Enabling Pattern-Aware Automated Map Generalization

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Abstract

In manual map generalization the cartographer's work is guided by a few principles such as selection of the essential content to meet the map's purpose, and preservation or accentuation of typical and unusual map elements. For instance in a topographic map for an urban area, urban building structures are considered to be typical elements. An example for an unusual element may be a group of ponds with regular spatial distribution and similar size that belong to a fish farm. The recognition and maintenance of such typical and unusual patterns is accomplished by a trained cartographer in an holistic manner. To automate this complex process it is necessary to transfer and decompose the cartographic knowledge and operations into a computer understandable form.

The *objective* of this thesis is to develop and test an approach that enables the maintenance of object relations and patterns during the automated map generalization process. In response to the drawbacks of existing approaches of maintaining map object relations and patterns, we present several requirements for improved approaches. One of these requirements is that structural knowledge (i.e. knowledge about existing patterns) should be explicitly modeled and attached to the map data, and not hidden in the generalization algorithms. A so-called *data enrichment* strategy such as this should allow a flexible and pattern-aware control of the generalization process. As a consequence of the flexible control approach we establish the *hypothesis* that the quality of the generalization result and the efficiency of the generalization process can be improved when the data enrichment strategy is employed.

The *conceptual framework* that we propose consists of five steps: The first step considers the identification of patterns and map object relations. In the second step the patterns are formalized using the relations. Subsequently the relations and patterns are extracted (step 3) and stored (step 4). Finally in step 5 the stored relations are utilized to enable pattern-aware decision making for generalization process control. Associated with these steps are the five *research questions* of this thesis: 1.) What types of relations exist in maps that can be used to describe patterns? 2.) How can we formalize these relations? 3.) How can we detect these relations? 4.) How can these relations be stored and the data be enriched? 5.) How can we exploit the enriched data for pattern preservation and process optimization? These research questions demand comprehensive answers that can not be elaborated thoroughly within the time frame of a PhD project. Hence, while the first research question is answered comprehensively in this thesis, we have chosen to answer the remaining questions with respect to two case studies that serve as a proof of concept of the 5-step framework. The first case study concentrates on the extraction and exploitation of urban structures such as inner city areas, urban areas, suburban areas, etc. In the second case study we aim to identify groups of islands.

The *contributions* of this thesis to map generalization research are essentially associated with the research questions. In response to the first research question we established a comprehensive typology of so-called horizontal relations (and patterns) that we derive from an analysis of topographic maps, thematic maps, and the cartographic literature. With respect to the second question

we show for both case studies how identification and formalization of patterns by use of horizontal relations can be accomplished. For the formalization of the island groups, which have been identified in a 'pencil and paper' experiment, we could utilize the Gestalt principles established by Max Wertheimer. To detect the urban structures (the third research question) we developed a supervised classification approach. For the recognition of large island groups formed by the perceptual principle of proximity, we developed an approach that utilizes a minimum spanning tree. The storage of relations, addressed by the fourth research question, has not been discussed in detail, but we use a graph structure and attribute values in the case studies. Finally we discussed for the islands example how relations can be exploited (the fifth research question). In order to *evaluate the hypothesis*, practical experiments have been conducted with expert generalization rules that account for the urban structure classification of buildings. We obtained an improvement in quality of the generalization result but could not clearly identify a gain in generalization efficiency. However, by accomplishing all five steps of the framework, we show its applicability and utility for the preservation of spatial patterns and relations during the map generalization process.

Based on the results and open problems that we discovered in our research, we identify three areas of *future map generalization research*: 1.) the further formalization and detection of relations and patterns, 2.) the revision and development of constraints to control the preservation of patterns, and 3) research on human computer interaction methods and tools to define and confirm patterns, and control the entire map generalization process more flexibly.

Zusammenfassung

Bei der manuellen Generalisierung von Karten wendet der Kartograph diverse Prinzipien an, wie die Auswahl von wichtigen Kartenobjekten, die für die Nutzung der Karte unabdingbar sind, sowie die Erhaltung und Betonung von typischen und ungewöhnlichen Kartensituationen. Typische Elemente einer topographischen Karte, die ein Stadtgebiet abbildet, stellen zum Beispiel die urbanen Gebäudestrukturen dar. Ein Beispiel für eine ungewöhnliche Kartensituation ist eine Gruppe von Seen, welche räumlich gleichmäßig verteilt sind und eine ähnliche Größe haben, da sie zur Fischzucht angelegt wurden. Die Erkennung und die Erhaltung solcher typischer und ungewöhnlicher Kartensituationen wird von einem gelernten Kartographen intuitiv und ganzheitlich durchgeführt. Soll dieser komplexe Vorgang automatisch von einem Computersystem erfolgen, dann müssen das kartographische Wissen und die kartographischen Vorgänge analysiert und in eine dem Computer verständliche Sprache übersetzt werden.

Ziel dieser Arbeit ist es, einen Ansatz zu entwickeln und zu testen, der die Erhaltung von Objektbeziehungen und räumlichen Mustern während des automatischen Kartengeneralisierungsprozesses erlaubt. Um die Nachteile bisheriger Ansätze zur Erhaltung von Mustern und Beziehungen zu vermeiden, werden diverse Anforderungen an den Ansatz gestellt. Eine dieser Anforderungen beinhaltet, dass strukturelles Wissen, also Wissen über existierende räumlichen Muster, explizit modelliert wird und die Kartendaten mit diesem Wissen verknüpft bzw. angereichert werden. Dies steht im Gegensatz zum derzeit üblichen Ansatz, bei dem das strukturelle Wissen im Generalisierungsalgorithmus verankert ist. Die von uns verwendete Strategie der Datenanreicherung soll eine flexible Kontrolle des Generalisierungsprozesses ermöglichen. Die sich daraus ableitende *Hypothese* der Arbeit beinhaltet, dass es möglich ist die Qualität der Generalisierungsergebnisse und die Effizienz des Generalisierungsprozesses zu steigern, wenn die Datenanreicherungsstrategie verwendet wird.

Die *Vorgehensweise* die wir für die Datenanreicherung in Verbindung mit dem Generalisierungsprozess vorschlagen besteht aus fünf Schritten. Im ersten Schritt werden die erhaltenswerten Muster und Objektbeziehungen identifiziert. Im zweiten Schritt erfolgt eine Formalisierung der Beziehungen. Danach werden die Beziehungen und Muster extrahiert (Schritt 3) und gespeichert (Schritt 4). Abschliessend werden im Schritt 5 die gespeicherten Beziehungen verwendet um eine angepasste Entscheidungsfindung bei der Kontrolle des Generalisierungsprozesses zu ermöglichen. Eng verknüpft mit diesen Schritten sind die fünf *Forschungsfragen* der Arbeit: 1.) Welche Typen von Beziehungen existieren in Karten, die bei der Beschreibung von georäumlichen Mustern helfen? 2.) Wie können die Beziehungen formalisiert werden? 3.) Wie können die Beziehungen erkannt werden? 4.) Wie sollten die erkannten Beziehungen gespeichert werden? und 5.) Wie können die angereicherten Daten verwendet werden um Muster zu erhalten und den Generalisierungsprozess zu optimieren? Diese fünf Fragen verlangen zum Teil sehr ausführliche Antworten, welche innerhalb des beschränkten Zeitraumes dieser Arbeit nur bedingt ausgearbeitet werden können. Aus diesem Grund wird in dieser Arbeit nur die erste Forschungsfrage ausführlich

beantwortet, während auf die verbleibenden Fragen anhand von zwei Fallbeispielen eingegangen wird. Diese zwei Fallbeispiele sollen die Zweckmäßigkeit des gewählten Ansatzes der Datenanreicherung aufzeigen. Das erste Fallbeispiel behandelt die Erkennung von städtischen Strukturen, wie z.B. Innenstadt, Stadtgebiet, Stadtrandgebiet, usw. In der zweiten Fallstudie sollen schliesslich Inselgruppen identifiziert werden.

Die *Beiträge* dieser Arbeit zum Gebiet der automatisierten Generalisierung von Karten sind eng verknüpft mit den Forschungsfragen. Als Antwort auf die erste Forschungsfrage wurde ein Katalog von horizontalen Beziehungen (und Mustern) erstellt. Dieser Katalog ist das Resultat einer Analyse von topographischen und thematischen Karten, sowie der kartographischen Literatur. Mit Bezug zur zweiten Forschungsfrage wird für beide Fallbeispiele gezeigt, wie Muster und Beziehungen identifiziert und formalisiert werden können. Speziell bei der Formalisierung von Inselgruppen, welche in einem Test mit mehreren Personen bestimmt wurden, erwiesen sich die von Max Wertheimer erarbeiteten Gestalt-Prinzipien als nützliche Grundlage. Zur Erkennung der urbanen Strukturen wurde ein überwachter Klassifikationsansatz entwickelt (Forschungsfrage 3). Um große Inselgruppen zu detektieren, die durch das Gestalt-Prinzip der räumlichen Nähe gebildet werden, wurde ein weiteres Erkennungsverfahren basierend auf einem "Minimum Spanning Tree" Ansatz entwickelt. Die möglichen Speichermethoden für Objektbeziehungen werden nicht ausführlich diskutiert (siehe Forschungsfrage 3). Allerdings wird in den Fallstudien zum einen eine Graphenstruktur und zum anderen die Speicherung als Attributwert verwendet. Mit Bezug auf die fünfte Forschungsfrage wird schließlich für das Inselgruppen-Beispiel theoretisch diskutiert wie die erkannten Beziehungen genutzt werden können. Die *Evaluierung der Hypothese* erfolgt durch praktische Experimente mit Expertenregeln für die Generalisierung, welche auf den urbanen Strukturklassen aufbauen. Die Ergebnisse der Experimente zeigen, dass eine Verbesserung der Qualität möglich ist. Allerdings konnte eine Steigerung der Effizienz nicht eindeutig bestimmt werden. Durch die Ausführung aller fünf Schritte mit den beiden Fallbeispielen haben wir gezeigt, dass der gewählte Ansatz der Datenanreicherung möglich und nützlich ist, um Objektbeziehungen und Muster während des Generalisierungsprozesses zu erhalten.

Auf Grund der Ergebnisse die wir während unserer Forschung an Methoden zur kartographische Mustererkennung und -erhaltung erzielten identifizieren wir *Forschungsbedarf* in drei Themenbereichen der automatisierten Kartengeneralisierung: 1.) die Formalisierung und die Entwicklung automatischer Methoden zur Erkennung von Beziehungen und Mustern 2.) die Prüfung und Entwicklung von Bedingungen (engl.: constraints) um die Erhaltung von räumlichen Mustern zu kontrollieren, und 3.) die Forschung an Methoden und Werkzeugen zur Interaktion des Computernutzers, um Muster zu definieren und zu bestätigen, sowie für die flexible Kontrolle des gesamten Generalisierungsprozesses.

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Stefan — Zürich, July 11, 2007

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Part I.

Synthesis

1. Introduction

Maps are part of our daily life: When we watch the weather forecast in TV, we see on the weather map how sunny, cloudy, or rainy it will be the next day. If we want to know which metro to take from the airport to the city center, we consult a metro map. Or; if we go hiking on our holidays and after three hours of walking we ask ourselves where exactly we are and where we can rest - then we consult a topographic paper map or, today's alternative, a digital map on a mobile device. These examples of our daily use of maps show that maps have different functions.
MacEachren (1994) lists four types of map functions in his book: 1 - exploration, 2 - confirmation, 3 - synthesis, and 4 - presentation. Some of these functions, such as presentation and exploration, are covered by the examples given above. To ensure that the map can fulfill its function, it must be made for those specific functions, that is: *made for the purpose*.

To generate maps which fulfill the intended purpose, we aim to utilize the technologies and methods that have been developed in the past years in the fields of computer science and geographic information science. By integrating and adapting the technologies to support *automated map generalization*, the research results presented in this thesis primarily aim to improve the *quality* of generated maps, and secondarily focus on increasing *efficiency* in map generation and production.

Map generalization is one of the components of the entire process of *map production* that includes data collection, data preparation and maintenance, map generalization, cartographic finishing, and (eventually) map printing. Manual as well as automated map generalization seeks to find a compromise between the two basic objectives that a map should meet. Firstly, the map should fulfill its specific purpose, and secondly, the map must be legible. Both objectives sound simple, but cause the cartographic dilemma: to balance information content against readability. Figure 1.1 shows the problem for a simple example where we aim to display the way from Zurich Main Station to the University of Zurich, Irchel campus, for a visitor of the Department of Geography. The image on the right of Figure 1.1 shows the complete way from the Main Station to the department building, with the same map data used to display the detailed surroundings of the Irchel campus and the Main Station on the left. The map showing the complete route is cluttered and hard to read in contrast to the detailed maps. It becomes clear that the map data must be treated in a special way if we want to use them for the overview image. The cartographic process which aims to solve the conflict between available map space, map legibility and the necessary map content to fulfill the map purpose is termed *map generalization*.

The International Cartographic Association (ICA) gives a concise definition of map generalization that also includes two necessary steps of data preparation: "[Map generalization is] *the selection and simplified representation of detail appropriate to the scale and/or purpose of the map*" (ICA 1973). This thesis will not provide a thorough introduction of the aims, principles, methods, and consequences of map generalization. For introductory articles and books we refer to Weibel and Dutton (1999), McMaster and Shea (1992), Buttenfield and McMaster (1991), Müller

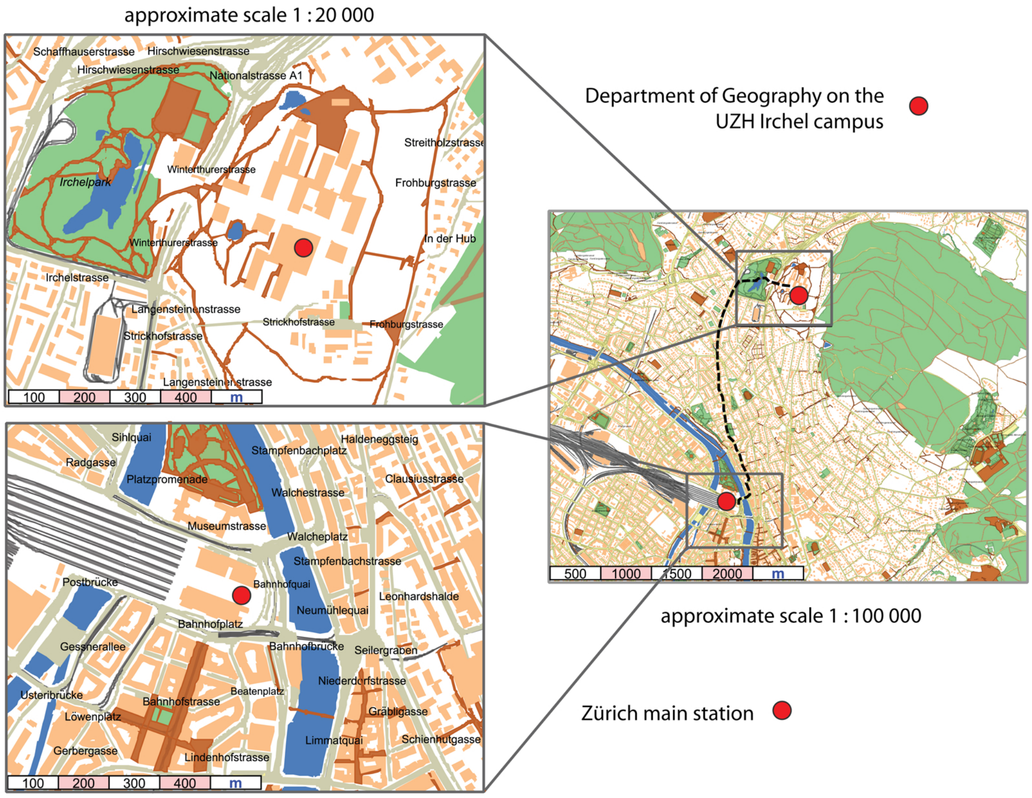


Figure 1.1.: Changing the map scale for an appropriate visualization to show the way from Zurich Main Station to the Department of Geography on the UZH Irchel campus. Simple scaling results in a cluttered, illegible map (right). No special attention was paid to street name labeling. (Data courtesy of the City of Zurich, Geomatik + Vermessung, 16.10.2007)

et al. (1995a), João (1998), and the recently published book by Mackaness *et al.* (2007). However, in Chapter 2 we provide the necessary background on map generalization for this thesis. In the following sub-sections we outline the motivation for our research and subsequently define the research objective, hypothesis and research questions.

1.1. The Motivation for Pattern-Aware Map Generalization

1.1.1. Two Examples of Pattern-Aware Manual Map Generalization

Two examples are given below which are intended to illustrate the need for *pattern-aware* automated map generalization. The *first example* considers the generalization of a group of four lakes and is shown in Figure 1.2. The four lakes have a common orientation towards the north-east and lie in close proximity. The selected target map scale requires the lakes to be generalized, since three of the four lakes are too small to be visible and the outlines of the lakes are too detailed for the target scale. A manual generalization of the four lakes applied by a cartographer will probably consist of three steps. In the first step the cartographer will analyze the situation and recognize that three of the four lakes are too small to be sufficiently legible, thus applying *geometrical knowledge* (Armstrong 1991). They will then analyze the situation further and recognize the common

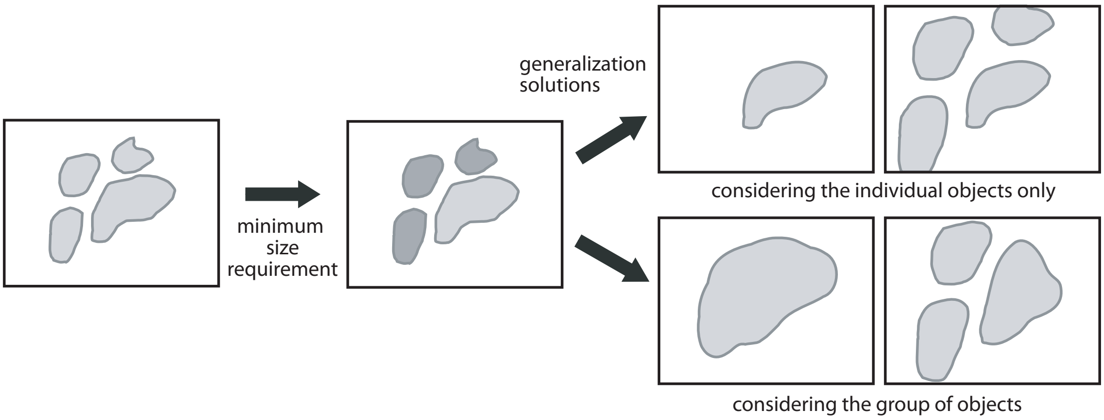


Figure 1.2.: Different generalization solutions for a group of lakes if contextual relations are ignored (top right) and observed (lower right).

orientation and the similarity in the shapes of the lakes. These properties make that the four lakes in Figure 1.2 are perceived as one organization. This step can be denoted as structural recognition leading to *structural knowledge* (Brassel and Weibel 1988, Armstrong 1991). Finally in the third step the cartographer will identify and apply cartographic operations to the lake group, such as lake elimination, aggregation and exaggeration, to retain a visually satisfying depiction of the lake group. The knowledge about appropriate cartographic operations that can be applied in a specific situation is denoted by Armstrong (1991) as *procedural knowledge*.

One important point in the manual generalization process applied by a cartographer is that the cartographer will first analyze the context, i.e. recognize the *visual pattern* of the lakes, and then generalize it in such a way that the visual pattern of the lakes is retained. Thus, structural knowledge and procedural knowledge influence the cartographer's decisions leading to a generalization solution. In Figure 1.2 we show several generalization solutions for the four lakes example. If we consider only the individual lakes and not the group, then either all the small lakes are eliminated and the large lake is retained, or all small lakes are enlarged until the minimum size is reached (Figure 1.2, top right). These solutions are not satisfactory since neither the visual pattern is maintained nor the area statistics are preserved (e.g. the ratio of lake area to land area). Only the generalization solutions shown in Figure 1.2, lower right, represent cartographically acceptable solutions.

The *second example* considers the different ways to generalize buildings on a topographic map, depending on whether they are located in a rural or an urban area. Generalization guidelines related to a specific urban context are described for instance in the textbook published by the Swiss Society of Cartography (SSC 2005). These guidelines aim at preserving the urban structures perceived by the map reader. The perceived urban structures evolve, for instance, from the interaction of building density and road patterns. In Figure 1.3 we exemplify the generalization of three buildings in the three cases A, B and C. All buildings are evaluated against existent geometrical knowledge to identify whether they need to be generalized. The analysis can be performed using three geometric legibility indices: building area (G1), building wall length (G2), and inner building width (G3). The evaluation determines that all three buildings need to be generalized. However, due to the available structural information - i.e. building A is located in a rural area,

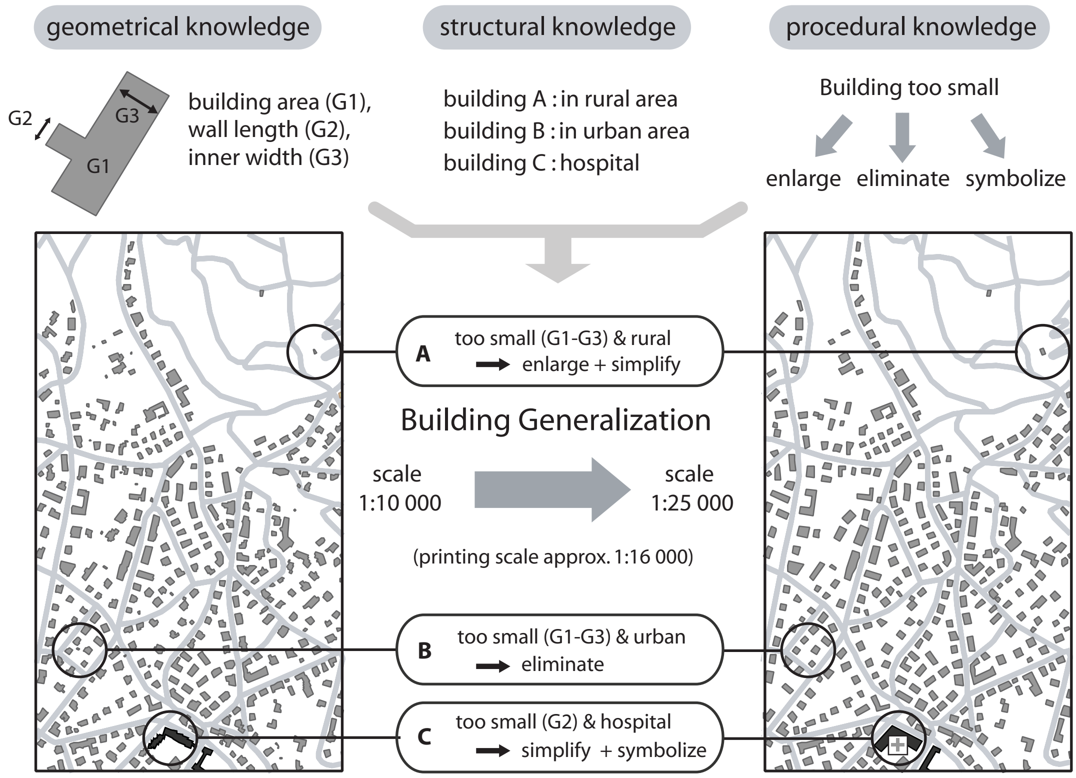


Figure 1.3.: Knowledge that contributes to contextual map generalization of buildings. (Data courtesy of the City of Zurich, Geomatik + Vermessung, 16.10.2007)

building B is located in an urban area, and building C is a hospital - the generalization operations that are applied are different for every building (see Figure 1.3). Again procedural knowledge and structural knowledge are used collectively by the cartographer to decide how an object or situation (i.e. a group of objects) is generalized. Thus, the preservation of the urban structure and the fulfillment of the map purpose can be achieved.

1.1.2. Problem Definition

In order to develop automated map generalization procedures, the geometrical, structural and procedural knowledge of the cartographer must be transferred into computerized form. Furthermore techniques have to be developed that utilize this knowledge to control the automated map generalization process. In the past two decades, map *generalization research* has addressed the following *topics* to formalize knowledge and build generalization systems:

- The *acquisition of knowledge* to identify the rules that guide the cartographer's work. For instance, such rules describe the priority order of positions to place name labels on a point, or demand that "roads leading to a building at the end of peninsulas, must not be omitted" (Weibel 1995, Kilpeläinen 2000, Duchêne *et al.* 2005).
- The *formulation of requirements* for a map (so-called *constraints*). For instance a building might need to be larger than $80m^2$ to be visible on a map of scale 1:25 000 (Beard 1991, Weibel and Dutton 1998, Galanda 2003a).

- The development of *generalization process models* that connect geometrical and procedural knowledge (Harrie and Weibel 2007). This could be done for instance by using rules and/or constraints.
- The development of *generalization algorithms* that realize cartographic operations such as line smoothing (Steiniger and Meier 2004), building simplification (Regnauld *et al.* 1999) or area aggregation (Bader and Weibel 1997).
- The development and adaptation of algorithms and *data structures* for the description of object configurations. These data structures should support generalization algorithms. Examples include the utilization of Delaunay triangulation for building displacement (Ruas 1998), the use of minimum spanning trees for building typification (Regnauld 2001), or the convex hull for line simplification (de Berg *et al.* 1998).

An analysis of the literature on these topics yields two *problems* with respect to generalization controlled by structural knowledge and maintenance of patterns. Firstly, existing algorithms for individual map objects (e.g. one building) rarely utilize structural knowledge describing the geographic context of the object. Thus, the object may be generalized inappropriately for its context. Secondly, in case of the generalization of several objects (e.g. a group of buildings) the structural knowledge is used, but it is hidden and 'hard coded' in the generalization algorithms. Hence, the algorithms often cannot be adapted for specific situations (e.g. rural vs. urban areas) or reused for similar generalization cases (e.g. a group of buildings vs. a group of lakes). Both issues raise the need for a more *modular* approach that accounts for three *requirements*:

1. The separation of the three types of knowledge to avoid structural knowledge being 'hard-coded' in generalization algorithms.
2. The explicit modeling of structural knowledge to allow multiple uses of acquired structural knowledge and generalization algorithms.
3. Enabling the connection of the three different types of cartographic knowledge, for the development of generalization strategies that account for the structural knowledge.

An approach that respects these conditions is expected to improve the quality of the generalization results due to the context dependent selection of generalization algorithms and parameters. It is additionally hoped that there will be efficiency gains for the generalization process, since fewer generalization trials (e.g. with different algorithm parameter settings) are needed to find a satisfactory generalization result. In Section 1.2 we propose a framework that strives to overcome the aforementioned problems.

1.1.3. Patterns and Pattern-Aware Map Generalization

After having introduced the motivation and problems underlying this thesis, we finally want to explain what is meant by *pattern-aware map generalization*. The term 'pattern' is used very widely in society and in different fields of research. For instance Merriam-Webster's Collegiate Dictionary (Encyclopædia Britannica 2007) lists 11 definitions for pattern, such as 1) form or model proposed for imitation, 2) a natural or chance configuration 3) a discernible coherent system based on the intended interrelationship of component parts, or 4) frequent or widespread incidence. Among the works that define the term 'pattern' explicitly for a specific discipline one can find the following definitions that may be of interest with respect to map generalization:

- Watanabe (1985, cited in Jain *et al.* 2000, pg. 4) defined in his book on pattern recognition a pattern "*as the opposite of a chaos; it is an entity, vaguely defined, that could be given a name.*" Jain *et al.* (2000) give examples related to Watanabe's definition, such as a fingerprint image, a handwritten word, and a speech signal.
- In a review of landscape metrics Gustafson (1998, pg. 144) states that he "*uses the term spatial heterogeneity and spatial pattern synonymously to refer comprehensively to the composition, configuration, and temporal aspects of* [landscape] *heterogeneity.*"
- Cha and Gero (1997, pg. 1), who have a background in architectural design computation, refer to a 'shape pattern' as "*a distinct and replicate syntax or compositional relationship between shape elements.*" Furthermore they regard a shape pattern as "*an invariant in shape objects that appears repeatedly in one object or in a set of objects.*"
- Fayyad *et al.* (1996, pg. 41) define a pattern for the field of data mining and knowledge discovery as "*an expression in some language describing a subset of the data or a model applicable to the subset.*"
- Equally with a perspective of data mining Hand *et al.* (2001, pg. 9) make a distinction between model and pattern. A model structure "*is a global summary of a data set*" that "*makes statements about any point in the full measure space*". [...] "*In contrast to the global nature of models, pattern structures make statements only about restricted regions of the space spanned by variables.*"
- Finally we consider it useful to add a definition of *perceptual organization* since pattern-aware map generalization invokes also perceptual organizations of map objects. With a background in computer vision Sarkar and Boyer (1993, pg. 382) identify perceptual organization "*as the ability to impose structural organization on sensory data, so as to group sensory primitives* [...] *with minimal domain knowledge* [...]".

Interestingly the term pattern is rarely explicitly defined in the domain specific literature that particularly addresses patterns. For instance Turner *et al.* (2001) treat the relationship between patterns and processes in landscape ecology, Marshall (2005) discusses "Streets & Patterns", or Miller and Han (2001) introduce geographic data mining methods for the exploration of (geographic) patterns. None of the authors defines the term 'pattern', but it becomes apparent what is regarded as pattern while reading these books. Often 'pattern' is implicitly defined by specifying the properties that a pattern should exhibit or by outlining the characteristics that discern different types of patterns. For instance Miller and Han (2001, pg. 4) refer to Fayyad *et al.* (1996) who assign an *interesting pattern* the following properties: non-randomness, validity (i.e. can be applied to new data), novelty (i.e. patterns are non trivial and unexpected), usefulness (lead to some action) and ultimate understandability (i.e. patterns are interpretable by humans). The characteristics that have been identified by Marshall (2005) as essential to distinguish among different types of street patterns are: composition (geometry), configuration (topology), and constitution (hierarchy).

After studying the numerous definitions and descriptions of 'pattern', we like to propose a definition of pattern with respect to map generalization. For this thesis we define a *pattern* as *a recognizable shape or arrangement of (geographic) objects that can be given a name*. Thus, a pattern shall be a 'typical arrangement' in that one can define a class or prototype from a family of similar arrangements. In this sense repetition is not a necessary condition for the specification of a pattern (i.e. repetition of geographic primitives that constitute a pattern), but it is a sufficient condition.

It may be worth distinguishing between two types of patterns: visual patterns and geo-spatial patterns. *Visual patterns* are the result of processes of perceptual organization, i.e. here specifically visual organization. Such patterns exhibit the Gestalt principles described in Wertheimer (1923), but without the use of domain knowledge. This means that during recognition of visual patterns the influence of the Gestalt principle of past experience is minimized, and that these patterns are visible to everyone. *Geo-spatial patterns* are patterns that are accessible only to persons with specific domain knowledge. They help the expert to infer ongoing or past environmental or social processes from pattern form. For instance, soil erosion is manifested in the rills and gullies it creates (Herweg 1996). For the case that a soil loss map is being compiled, the soil scientist will identify the rills and gullies, and their relation to each other as 'important' features. These need to be depicted in the map derived (by generalization) from the data, since the pattern that has been generated by several individual rills enables the soil erosion process to be inferred by the expert that reads the map.

Both types of patterns can be considered as structural knowledge since they influence the way a map is designed by cartographers. We denote the map generalization process as *pattern-aware* map generalization, if inherent patterns that are important for the intended map use are preserved or even emphasized during the generalization process.

Besides the term pattern we also use the term *relation* throughout this thesis. A relation denotes a certain configuration among two or more map objects of a single map in terms of geometry, semantics, topology, statistics and structure. Relations can not be composed entirely by other relations and should be considered as the atomic elements that constitute patterns. For instance an alignment of buildings - a visual pattern - may be identified due to the geometric and semantic relations between the buildings, such as 1) similar ground area size, 2) similar distances between the buildings, 3) similar building orientation, and 4) same building use: 'residential housing'. Thus, our relations are comparable to the geons, a set of geometric primitives, which are a fundamental element of Biederman's theory of 'recognition-by-components' (Biederman 1987). By introducing relations to formalize patterns we should be able to discern between different types of patterns.

The *focus* of this thesis will be on relations and static patterns that exist within one map scale, also denoted as horizontal relations and patterns (Neun and Steiniger 2005, see Section 4.1). Horizontal relations are used to formalize a pattern that occurs within one map scale. Thus, we will not address patterns over scale and/or time and will not analyze changes of patterns over different scales and times.

1.2. Objective, Methodology and Research Questions

The *key objective* of this thesis is to develop an approach that enables pattern-aware map generalization. The approach is firstly required to be modular, so that the different types of knowledge are separated. Secondly, structural knowledge must be explicitly modeled and not hidden in the algorithms. And thirdly the approach should be able to link geometrical and structural knowledge on the one hand, and both types of knowledge to procedural knowledge on the other hand, to enable an informed control of map generalization.

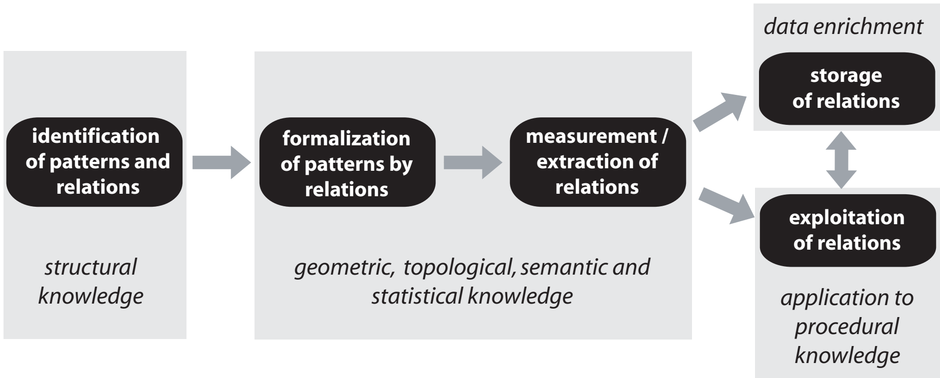


Figure 1.4.: A 5-step framework to enable pattern-aware automated map generalization.

The *methodological approach* that we propose and that we aim to test in this thesis, will formalize structural knowledge explicitly, attach it to the data to be generalized, and then utilize the structural knowledge in conjunction with procedural knowledge. This approach to make knowledge explicit and enrich the data with this knowledge is known as *Data Enrichment* (Ruas and Plazanet 1996). Weibel and Burghardt (2003), and also Neun *et al.* (2004), describe data enrichment as ”[a necessary process] *to equip the raw spatial data with additional information about the objects and their relationships*.” Weibel and Burghardt (2003) identify several possibilities for the exploitation of the attached structural and geometrical knowledge:

- It enables the preservation of patterns and relationships during the generalization process that are critical for the purpose of the final map.
- It helps algorithms to be selected that are appropriate to the context of the object or the group of objects.
- It can be used to select different parameter values for algorithms according to the context.
- It enables a context related automated evaluation of the results.

Thus, the data enrichment strategy on the one hand meets our three requirements, and enables an informed generalization control on the other hand, which subsequently will support the appropriate treatment of spatial patterns. To implement the data enrichment strategy in the map generalization process we propose a conceptual framework that consists of the five components shown in Figure 1.4. Each component can be considered as one step of the data enrichment and exploitation process. In the first phase it is necessary to identify the patterns that are of interest and the relations that can describe these patterns. In the second step we formalize the patterns using the relations. The third step consists of the pattern recognition process based on the extraction of the relations. Once we have extracted a pattern it has to be stored for the exploitation phase. Thus, we enrich the data with the relations. Finally, in the last step, the stored relations can be utilized to enable appropriate decision making for the control of generalization process.
The *hypothesis* that we derive from our key objective is formulated as follows:

> ”Data Enrichment enables a pattern-aware map generalization that results in an improvement of the quality of the generalization results and in an improvement of the efficiency of the generalization process”.

In addition to testing this hypothesis, a set of research questions were addressed. The questions are directly associated with the five steps of the conceptual framework:

1. What types of relations exist in maps that can be used to describe patterns?
2. How can we formalize these relations?
3. How can we detect the relations?
4. How can relations be stored and the data be enriched?
5. How can we exploit the enriched data for pattern preservation and process optimization?

These research questions demand comprehensive answers that can not be elaborated thoroughly within the time frame of a PhD project. Hence, while the first research question will be answered comprehensively in this thesis, we have chosen to answer the remaining questions with respect to selected examples of patterns and relations. The examples that have been selected and the resulting structure of the thesis will be described in the next section.

1.3. Structure of the Thesis

This thesis is based on four research papers that address the research questions and parts of the presented framework in different aspects. Two of the research papers have been accepted by international scientific journals and one paper has been submitted to a further journal. The fourth paper has been presented at the ACM-GIS 2006 conference based on a peer review of the full paper. The four publications ordered by their presentation in Part I of this thesis are as follows:

Research Paper 1	Steiniger, S., and R. Weibel (2007): Relations among map objects in cartographic generalization. *Cartography and Geographic Information Science*, Vol. 34, No. 3, pp. 175-197.
Research Paper 2	Steiniger, S., T. Lange, D. Burghardt and R. Weibel (in press): An approach for the classification of urban building structures based on discriminant analysis techniques. *Transactions in GIS*.
Research Paper 3	Steiniger, S., P. Taillandier and R. Weibel (submitted): Utilising urban context recognition and machine learning to improve the generalisation of buildings.
Research Paper 4	Steiniger, S., D. Burghardt and R. Weibel (2006): Recognition of island structures for map generalization. In: *Proceedings of the 14th Annual ACM International Symposium on Advances in Geographic Information Systems*, ACM-GIS'06, Arlington, Virginia, pp. 67-74.

As mentioned above we aim to answer the research questions of this thesis with respect to *two selected case studies*. These case studies will serve *as a proof of concept* for our framework.
The choice of the two case studies has been governed by the following principles:

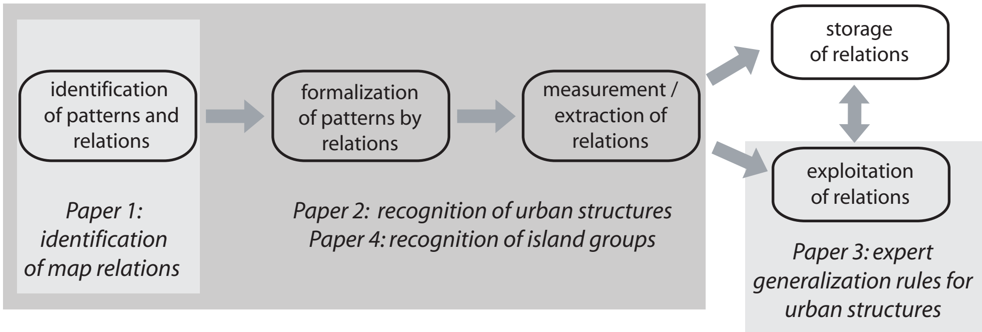


Figure 1.5.: The 5-step framework and the papers of the thesis.

- The formalization and recognition steps are demonstrated for spatial patterns existent in thematic and topographic maps.
- The patterns should be simple, in that they involve only one map theme (e.g. water bodies, buildings), to enable an easier analysis of problems related to pattern formalization, detection and utilization.
- Both case studies should address different types of patterns, such as patterns that emerge from semantic concepts and patterns that are generated by visual stimuli.

Therefore, the first case study concentrates on the extraction of urban concepts such as inner city areas, urban areas, suburban areas, etc. Such patterns are related to a semantic concept (Research Paper 2 and 3). In the second example that is presented in Research Paper 4 we aim at identifying groups of islands. These organizations emerge from perceptual processes in the human mind. In Figure 1.5 the parts of the framework that are covered by the research papers are shaded in gray.

This thesis consists of *two major parts*: Part I, the *synthesis*, covers an introduction of the topic, presents the theoretical background and the state of the art, summarizes the papers and discusses the results and future perspectives. In Part II, the *research papers* are presented in their most current manuscript form. Note, that links from Part I to the publications of Part II are established by use of the paper number.
The chapters presented in the synthesis cover the following content:

Chapter 1 *Introduction*: The thesis starts by introducing the issues of automated map generalization. The motivations for this research are given and important terms are defined. Finally the key objectives and the research questions are presented.

Chapter 2 *Theoretical Background*: This chapter provides an overview of the approaches and necessary components of automated map generalization. The short review specifically focus on generalization principles, requirements, cartographic operations and process modeling approaches.

Chapter 3 *State of the Art*: Here the publications of related disciplines and map generalization research on spatial pattern analysis and data enrichment are reviewed. The chapter concludes with the research challenges that we address in this thesis.

Chapter 4 *Summary of Papers*: We present in a summarized form the methods and results of the four research publications. For every paper we separately present the objectives and discuss the contributions to map generalization research.

Chapter 5 *Discussion*: The chapter revisits the research questions formulated in Chapter 1. We then evaluate the hypothesis with respect to our research results.

Chapter 6 *Conclusion*: In the final chapter we summarize the main contributions of the thesis to map generalization research and identify other fields to which the methods and results may contribute. Finally we identify needs for future research with respect to the results of this thesis.

2. Theoretical Background on Automated Map Generalization

Map production, including map generalization, can still be considered a craft carried out by trained cartographers and domain experts, for instance a geologist in the case of a geological map. Like in other domains of industry, the replacement of manual processes by *automated procedures* is of key interest to National Mapping Agencies (NMA's) and private cartography companies. The integration of automated processes into map production has several motivations: Firstly, the update cycle of one map sheet for topographic maps, produced by NMA's, takes approximately five years due to the time consuming manual procedures. For instance Kreiter (2006) reported that at Swisstopo (the Swiss national mapping agency) the time between the aerial pictures taken and the printing of the map can take between one and a half and three years. Secondly, the generalization tasks executed by cartographers are subjective, hence may be solved differently by different cartographers (Kilpeläinen 2000). Thirdly, manual editing results in lower positional accuracy of map objects compared with computer methods (McHaffie 2002). Finally the fourth point is that the development of new map products is difficult due to time and budget constraints. Thus, all these considerations are in opposition to today's need for *timely*, *standardized*, and *accurate* geographic data and *maps*.

This chapter explains how the generalization process works and how an automated generalization approach can be realized. In the first section we outline the cartographic principles and discuss their decomposition to enable an automated generalization process. We introduce the requirements expected from a map and the types of operations applied by cartographers during map generalization. We review the conceptual process models that have been developed to describe and automate the overall map generalization process. In the second section we discuss the approaches for automated map generalization that have been used so far in research and practice.

2.1. Decomposing Manual Map Generalization for Automation

2.1.1. Cartographic Principles

Manual and automated map generalization both pursue the same two basic objectives that have been exemplified in Chapter 1. Firstly, the map should be designed to fulfill a specific purpose, and secondly, the map must be legible. To achieve these goals the map generalization process is guided by a few general principles, which are:

- to select the essential content and omit unimportant elements,
- to preserve and emphasize the typical and unusual elements, and
- to simplify, making the map readable.

These principles are intuitively applied by a trained cartographer but need to be decomposed and reformulated for automated map generalization. A decomposition is necessary to specify exactly what is meant by the terms: readable, typical, unusual, and important. It further covers the definition of algorithms and application principles for the mentioned operations: select, preserve, emphasize and simplify. Finally, it is necessary to reformulate the principles in a language which enables the generalization process to be executed by a computer, for instance by formulation of *IF condition THEN action* rules. In the following four sub-sections we will address the decomposition of requirements and operations, and review the approaches of knowledge modeling that enable map generalization to be automated.

2.1.2. Cartographic Knowledge Acquisition to Achieve a Decomposition

To be able to treat the generalization process in a rule like manner, one needs to identify the map situations that require generalization and to identify the cartographer's actions that correspond to a particular situation. An automated classification of map situations in terms of object configurations that are considered as being typical, important, or illegible requires in the first place *knowledge acquisition* from an expert (cartographer). A number of methods to retrieve knowledge from cartographers are discussed in Weibel *et al.* (1995) and Kilpeläinen (1997, 2000). Standard methods, where knowledge is directly gained from the human expert, are: interviews, group discussions, questionnaires or forms, learning by instruction, and learning by observation (Weibel *et al.* 1995). For instance Kilpeläinen (2000) reports on the results obtained from interviews with cartographers and the use of forms. Other, indirect, methods that can be used include the analysis of cartographic text books (e.g. SSC 2005), the comparison of map series, machine learning techniques to acquire rules and classifications, and process tracing in interactive systems. Müller (1990), Leitner and Buttenfield (1995) and Timpf (1998) have for instance analyzed map series. The use of machine learning methods is described in Weibel *et al.* (1995), Reichenbacher (1995), Plazanet *et al.* (1998) and Sester (2000b). Similar to the latter, Duchêne *et al.* (2005) report on a learning tool to classify buildings after examples are provided by an expert.

Although we can list a number of methods for knowledge acquisition, it has to be pointed out that acquiring the knowledge from experts is time consuming and may give ambiguous results. Compton and Jansen (1990) illustrate the problems of ambiguity very clearly in the following citation[1]:

> "If the knowledge engineer takes a difficult case [i.e. situation to generalize] to two experts independently, he [or she] will get two fairly simple, but sometimes slightly different rules [on how to generalize][...]. If the knowledge engineer then brings the expert together and asks which rule is right, a very complex discussion is liable to ensue, as the experts (politely) attempt to prove to each other that their rule is better, normally resolving the question, by agreeing that their rules apply in different contexts and are complementary."

The diversity of possible generalizations generated by human cartographers has been shown by Kilpeläinen (1997, 2000) when she compared the results between several cartographers and a textbook reference. Usually one attributes these differences in the results of manual generalization to the creative component of map generalization. The existence of this creative component is

[1]Text in squared brackets added by the author of this thesis.

proof to some cartographers that it is not possible to produce maps with automated methods that approach the quality of manually generalized maps. But it is also proof to others that manually created maps are inconsistent and inaccurate.

2.1.3. Cartographic Requirements

In the literature on knowledge acquisition reported above (e.g. Müller 1990, Kilpeläinen 2000), and also from analysis of cartographic textbooks, several requirements on the display of map objects have been identified. Kilpeläinen (1997, 2000) distinguishes four types of cartographic rules, and thus four conditions to ensure the purpose of the map and its legibility: geometrical, topological, contextual, and cultural requirements. We will explain these types and add a further type of so-called procedural requirements that are important for the automated process:

- *Geometrical requirements* - These requirements specify size thresholds on the geometry dictated by human perceptual limits. Examples of these limits for a single map object are the minimum size for areas, the minimal length of a line or building wall, and the minimum symbol width of lines. With respect to several map objects, a minimal separation distance between those is necessary to be able to visually distinguish the objects. Geometrical requirements force transformations of objects, being *active* constraints. *Passive* constraints are also common such as maintaining positional accuracy if displacement operations are applied, or preventing excessive shape deformations when objects are simplified. The latter type appears only in an automated processing context, since for manual generalization the cartographer intuitively understands these limitations and applies them implicitly.
- *Topological requirements* - Topological conditions are used to preserve the relationships in terms of connectivity, adjacency and containment between map objects. They are necessary since geometric transformations applied by the cartographer may alter the topology. A well known example for a topological requirement is that a building should not be on the opposite side of the road after the generalization process.
- *Contextual requirements* - These requirements usually extend over several objects. They should help to maintain the spatial and semantic structure of the map. Therefore they are also termed as *structural constraints* by some authors (e.g., Weibel and Dutton 1998). Within the context of this thesis, they represent constraints that help to preserve spatial patterns. Examples are specifications that demand the maintenance or emphasis of alignments (e.g. houses in a row), or stipulate the preservation of size relations between neighboring map objects, or require the maintenance of object density relations across larger areas of a map.
- *Cultural requirements* - Examples for this type of requirement are provided by Kilpeläinen (2000). A cultural requirement is for instance expressed by a rule specifying that place names of historical value should not be omitted. These requirements are highly application dependent and often focus on thematic mapping. Within the context of topographic and thematic maps emerge cultural requirements from the traditional styling of maps (e.g. symbols and colors used), which usually differ from country to country. According to Kilpeläinen (2000) is the difference between the cultural and contextual requirements that cultural requirements depend exclusively on non-spatial attribute information.
- *Procedural requirements* - This type of requirement defines for instance the order of processing thematic layers of the map (e.g. first generalize roads, followed by buildings). But

this type also comprises constraints on the sequencing of generalization operations such as simplify the line first and smooth afterwards. Weibel and Dutton (1998) note that these requirements can be hard to identify, but may in fact be rather simple and reflect cartographic practice. Thus, the requirements sometimes express guidelines that a cartographer simply knows from textbooks or past experience, whereas the computer does not have experience.

Several other classifications of requirements have been proposed for specific applications (Ruas and Plazanet 1996, Weibel and Dutton 1998, Harrie 1999, Galanda 2003a). For instance the typologies of Ruas and Plazanet (1996) and Harrie (1999) focus on the graphical aspects of map generalization. Galanda (2003a) considers exclusively requirements for the generalization of categorical maps that contain only polygonal objects. Thereby it is important to note that in the generalization literature the mentioned requirements are usually called *constraints*, reasoned by their kind of formalization and realization in automated generalization (see Sub-Section 2.2.2 below). If one of the mentioned requirements is not fulfilled, then one usually denotes this as violation of a requirement and *cartographic conflict*. The degree of fulfillment is expressed by the *satisfaction* measure (see Research Paper 3).

2.1.4. Cartographic Operations

When describing the cartographic principles above we have already used terms for cartographic actions such as select, omit, preserve, emphasize and simplify. Whereas select and omit can be seen as counter-parts, and may be expressed as an elimination operation, the other operations consist rather of a multitude of individual processes or comprise different actions in different contexts. For instance the simplification of lines that represent roads may demand methods and principles different from the simplification of building outlines. Similar to the cartographic requirements a number of cartographic operations could be identified using knowledge acquisition techniques such as observing experts and analyzing textbooks. Whereas in the textbooks by Hake *et al.* (2002) and Robinson *et al.* (1995) a number of basic cartographic operations are mentioned Shea and McMaster (1989) have elaborated on these, providing a comprehensive list of operations. Thereby they describe the operations extensively and further differentiate between point, line and area operations. Other authors have added operations and refined definitions of operations (Plazanet 1995, Ruas and Lagrange 1995).

It is worth to note that in the cartographic community no common agreement on the association between cartographic actions and terminology exists. This has been shown by Rieger and Coulson (1993) who asked several cartographers to explain terms such as 'simplification' or 'smoothing'. A number of cartographers could not see a difference between some of the terms or did not know what was meant by a specific term (e.g. typification). Therefore, instead of simply naming the operations, we give a list and a description of operations in Table 2.1. This list extends the set of operations presented in Galanda (2003b) that primarily focus on the generalization of area objects.

A last aspect to be mentioned with respect to cartographic operations is that operations describe manual procedures of a cartographer. In a computer based generalization system, the operations have to be implemented in the form of a specific algorithm. Thereby several algorithms based on different mathematical models can be used to realize the same cartographic operation computationally. Take for example the displacement operation as applied to buildings. Bader (2001) presents a physically motivated approach using elastic beams and an approach based on a ductile truss generated from a minimum spanning tree; Ruas (1998) a Delaunay triangulation based approach; and Højholt (2000) an approach based on the Finite Elements Method. A useful overview and discussion on operations and algorithms is provided by Regnauld and McMaster (2007). Several algorithms for map generalization are described in Li (2006).

Table 2.1.: Generalization operations, extended from Galanda (2003b).

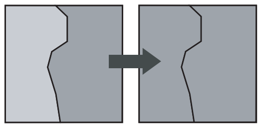
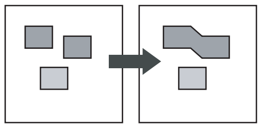
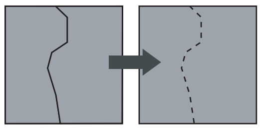
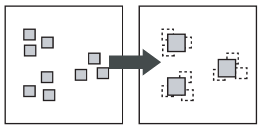
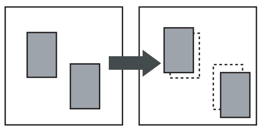
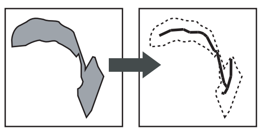
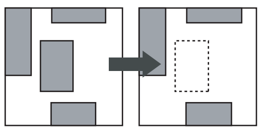
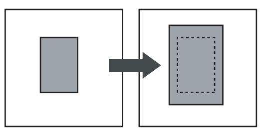
Semantic transformation		
Reclassification	Changes the class of an object. Usually one reclassifies to a more abstract class, e.g. an area of deciduous forest to forest.	
Spatial transformation of several objects		
Aggregation	Combines disjoint map objects to one new object by bridging the space between them.	
Amalgamation / Merge	Combines adjacent objects to one new object.	
Typification	Reduces the complexity of a group of objects by eliminating, displacing, enlarging and aggregating the individual objects, whereby the typical object arrangement is maintained.	
Displacement	Denotes the movement of an entire object. The object's shape remains unchanged. (see also Exaggeration)	
Spatial transformation of one object		
Collapse	Collapses a polygon either to a line or to a point. The example shows a polygon collapse to the medial axis.	
Elimination	Defines the removal of one or more objects from the data set. The freed space may be assigned to neighboring objects, or left empty.	
Enlargement	Denotes a global increase of an object.	

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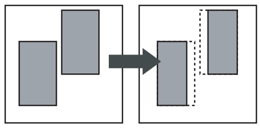
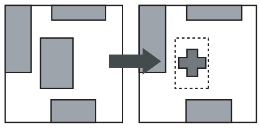
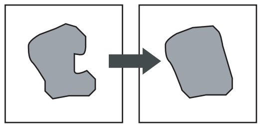
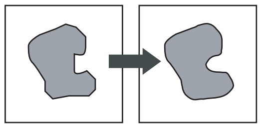
Table 2.1 – continued from previous page

Exaggeration	Defines a local displacement of object parts, leading to shape distortion. It can be induced by distance conflicts with other objects or by internal distance conflicts. (Note: Exaggeration is closely related to displacement)	
Symbolization	The visual representation of the footprint of an object is replaced by a (pictorial) symbol.	
Spatial transformation of a line object (including the outline of polygons)		
Simplification	Reduces the granularity of an outline by removing insignificant crenulations.	
Smoothing	Improves the visual appearance of an object's outline.	

2.1.5. Conceptual Map Generalization Models[2]

After decomposing the generalization principles into cartographic requirements and operations, the question remains of how these elements can be tied together in a comprehensive generalization process model. Therefore, the steps executed mentally and manually by a cartographer have to be analyzed to build conceptual models of the generalization process. The first conceptual models to be developed were *process oriented models*, such as the ones from Brassel and Weibel (1988), and McMaster and Shea (1992). Later on, Ruas and Plazanet (1996) developed a *hierarchical* generalization model. This model still draws from the manual generalization approach but can be more easily realized with computational models that have been developed in areas of artificial intelligence and machine learning. In the next two sub-sections we will the review some of the existing models.

Process Oriented Models

The conceptual generalization framework presented by Brassel and Weibel (1988) distinguishes five stages of processing: (a) structure recognition, (b) process recognition, (c) process modeling, (d) process execution, and (e) data display (see Figure 2.1). The generalization process starts with *structure recognition* on the source data that is constrained by the generalization controls (e.g. map purpose, scale, symbol specifications, etc.). The objective of that phase being a characterization of spatial and semantic relations between the map objects and their aggregates. *Process recognition*, the second step, is also constrained by the generalization controls and aims to deliver information

[2]This subsection is based on material presented in Steiniger and Weibel (2005a)

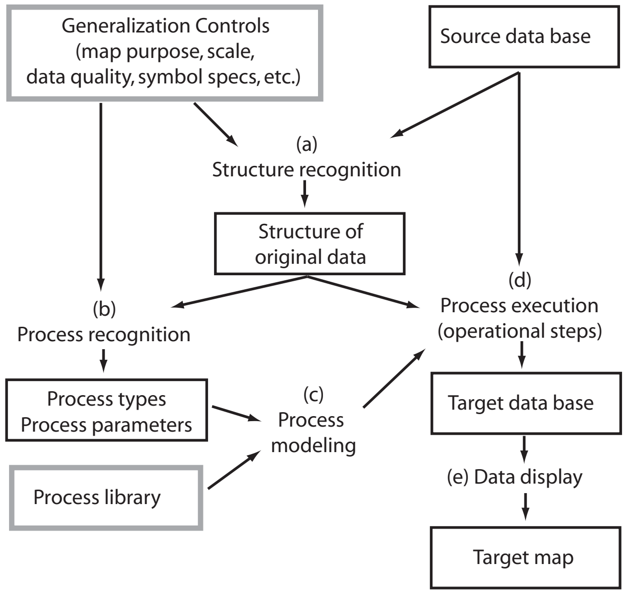


Figure 2.1.: The conceptual framework of map generalization by Brassel and Weibel (1988).

about process types (a synonym used for the cartographic operations of the preceding section) and parameters to apply to the previously characterized data. In the third step, *process modeling*, the compilation of rules (see below) and procedures from a process library is made. The fourth step, *process execution*, is responsible for the execution of the compiled set of data transformations (i.e. generalization procedures), followed by the final step, *data display*, responsible for displaying the previously transformed data.

Whereas this conceptual framework advocates a sophisticated generalization process based on the characterization of the structure and meaning of the source map data, most generalization algorithms until the mid-1990s only used simple built-in heuristics for data characterization (i.e. structure recognition). However, in recent years this has changed with generalization approaches that build on explicit data characterization, such as the one used in the AGENT project (Lamy *et al.* 1999, Barrault *et al.* 2001).

The model by Brassel and Weibel (1988) has been extended by McMaster and Shea (1992). They added missing parts and specified details for the process phases. The framework by McMaster and Shea (1992) is built around the questions: "Why, when and how to generalize?". The first question - "*Why to generalize?*" - addresses philosophical objectives similar to our description of map generalization, e.g. reducing the complexity and fulfilling the map purpose. But the question also covers the requirements that lead to automated generalization approaches, such as maintaining (spatial) accuracy and ensuring a consistent application of generalization rules. The second question - "*When to generalize?*" - covers the geometric evaluation of the map data and can be related to the geometrical knowledge, such as in Armstrong (1991). Finally, the question - "*How to generalize?*"- induces a decomposition of the generalization actions of the cartographer. Here, a certain number of geometric and attribute transformations have been identified, such as classification, symbolization, simplification, smoothing, aggregation and so on, that are performed by cartographers.

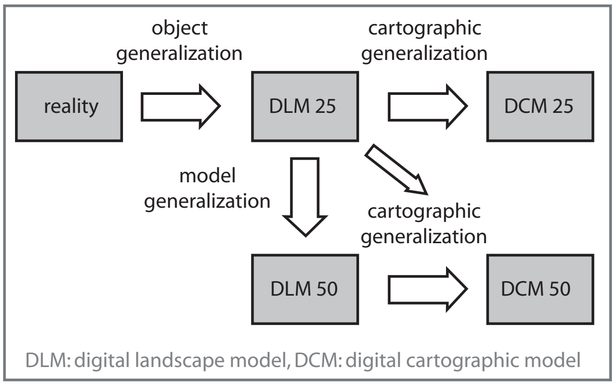


Figure 2.2.: The generalization types of the German ATKIS project. The numbers denote the resolution scale in thousands (e.g. 25 equals 1:25 000).

The generalization model used in the German ATKIS project (Grünreich 1985, Morgenstern and Schürer 1999)) represents a different view of the overall generalization process. Here, a distinction into three types of generalization processes is made (Figure 2.2). The first type is called *object generalization* and describes a mental generalization process accomplished by the person collecting the data (surveyor, aerial photo analyst, or data analyst) in terms of abstraction and selection from reality to data. A second type of generalization - *model generalization* - aims to reduce the resulting dataset of object generalization under statistical control. Thereby a reduction is achieved by decreasing the number of object classes and by decreasing the spatial and attribute resolution. Model generalization may also include geometry type changes, such as collapsing an area to a line. *Cartographic generalization* denotes the third process type. Here, the objective is a graphic representation of the digital data. Therefore symbolization specifications are applied and structures are modified locally by considering the map object characteristics (e.g. application of elimination, exaggeration, displacement, etc.).

Hierarchical Modeling

To consider map generalization as a hierarchical process has been proposed by Ruas and Plazanet (1996). Their model is partly based on the model of Brassel and Weibel (1988) using the parts of structure recognition, process recognition, process modeling, and execution. They additionally assimilate the suggestion by Mackaness (1995b) that only an iterative refinement strategy with *trial and error* (i.e. backtracking facilities) results in a satisfactory map. The model not only integrates operations, but also integrates algorithms to provide realizations of specific cartographic operations. This is due to the fact that the model has been developed after first gaining experience with interactive generalization systems. Such systems already supplied various different algorithms for each operation (e.g. several algorithms for line simplification).

The proposed framework consists of three levels of processing (see Figure 2.3): On the highest level a 'global master plan' determines a sequence of generalization tasks to apply on the level of the entire map (e.g. aggregate all adjacent objects of the buildings class). On the middle level a geographic '*situation*' is selected according to the given task (e.g. the objects contained in an urban block). Finally on the local level, the following iterative process starts:

1. *Analysis* of the situation using the requirements (i.e. constraints). If a requirement is vio-

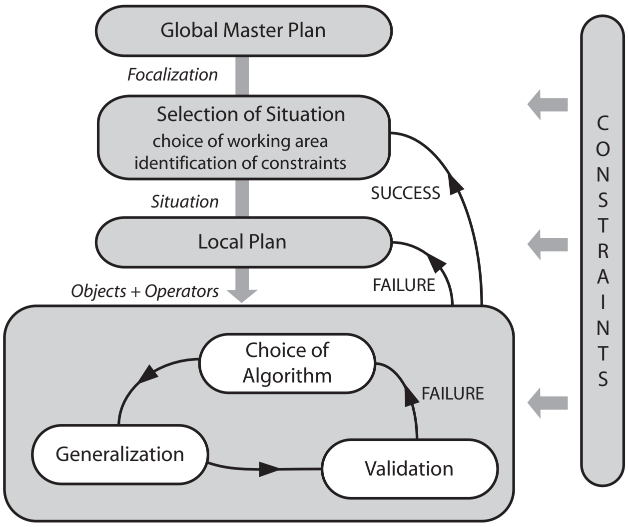


Figure 2.3.: The hierarchical generalization model, slightly modified, after Ruas and Plazanet (1996).

lated, the steps 2-4 have to be executed, otherwise a new situation is selected.

2. *Choice* of operations (algorithms) and their sequence, such that the requirements are satisfied if the algorithms are applied.
3. Generalization of the situation or object by *execution* of algorithms.
4. *Evaluation* of the generalization result. If the requirements are satisfied, then a new situation is chosen. Otherwise different operations, algorithms and order of execution are chosen.

The process is continued on the local level until a satisfactory generalization result is obtained. The model is not only a conceptual model but was also initially implemented on an experimental platform at IGN France called Stratège. Later this model was refined and re-implemented in the prototype generalization system of the AGENT project (Lamy *et al.* 1999, Barrault *et al.* 2001) and its commercial successor *Radius Clarity*™[3].

Finally a further hierarchical model was proposed by Peter and Weibel (1999) with a particular focus on the generalization of categorical maps. It is strongly influenced by the frameworks of Brassel and Weibel (1988), McMaster and Shea (1992), and Ruas and Plazanet (1996). Peter and Weibel (1999) discussed in detail generalization operations and requirements for categorical maps and proposed measures for their evaluation. A unique element is the data model specific view, distinguishing generalization operations and measures in the raster and vector domain, as well as hybrid raster-vector methods.

2.2. Approaches to Automated Map Generalization

Over the past two decades several attempts to develop comprehensive automated generalization systems have been reported. We will give a short overview of these approaches with respect to the historical development. Generally we will distinguish the following five approaches:

[3]Software *Radius Clarity*: http://www.1spatial.com/products/radius_clarity/index.php

- Interactive Systems
- Rule-Based Systems
- Workflow Systems
- Multi Agent Systems
- Optimization Approaches

Although multi agent systems can also be seen as an optimization approach, we will consider them separately, since the approach involves other computational techniques as well (e.g. self organization, distributed problem solving, communication, learning) and results present not necessarily an optimal solution. Furthermore we will also outline that more than one optimization approach has been used for map generalization. For a detailed overview of the different modeling approaches we refer to Harrie and Weibel (2007).

2.2.1. Interactive Systems and Rule-Based Systems

It has been previously pointed out that the acquisition of cartographic knowledge is difficult. This is due to the fact that the cartographer is often unaware of the steps of their reasoning process, because the reasoning seems so obvious (Kilpeläinen 2000). Therefore a simplistic way in the advent of map generalization systems has been to leave the complete decision process in the cartographer's hands. Thus, the generalization system provides a set of digital generalization tools that are interactively selected and applied by a cartographer. This way of using the cartographer's knowledge is called *human interaction modeling* (Harrie and Weibel 2007). However, for some of the tasks to be solved during the generalization process, the formulation of requirements and actions is not as hard as for the artistic components of map making. Examples are legibility rules for ensuring minimal dimensions of object size and inter-object distances. Rules such as *IF* (area of building $X \leq 200m^2$) *THEN* (apply enlargement algorithm) could be fairly easily accomplished by a computer. Thus, in the late 1980s and early 1990s research focused on the development of rule-based expert systems. This approach requires the generalization process to be broken down into condition-action pairs. Hence, the approach is also termed *condition-action modeling* (Harrie and Weibel 2007). Examples for the development of rule-based generalization systems have been reported by Nickerson and Freeman (1986), Nickerson (1988) and Schylberg (1993), plus a rule-based system for name placement by Jones (1989).

2.2.2. From Rules to Constraints

Both approaches, i.e. interactive generalization systems and rule-based systems, have their disadvantages. An evaluation of interactive generalization systems shows a very low productivity gain on the one hand, and on the other hand that the generalization results mainly (and not surprisingly) depend on the skills of the user (Ruas 2001). A weakness of rule-based systems is the difficulty of acquiring and formalizing (cartographic) rules in a consistent manner (Compton and Jansen 1990). Another disadvantage is the large number of rules required to describe requirements and actions between map objects sufficiently well. Further problems arise from the sequencing of generalization operations, since the different operations may affect each other and potentially cause secondary conflicts. For example one geometric condition demands the simplification of a complex building outline, while at the same time a size condition requires an enlargement of the building to be visible on the map, and finally a third condition will not allow a building enlargement due to an resulting geometry overlap with a neighboring building. Thus, a need exists for a flexible sequencing approach that must be capable of handling several requirements at the same time (Harrie and Weibel 2007, Holland 1986/1995 interpreted by Armstrong 1991).

Prompted by the drawbacks of rule-based systems Beard (1991) proposed the use of *constraint-based* modeling for automated generalization. *Constraints* formulate requirements of a generalized map, that is, conditions that a generalized map should adhere to. However, in contrast to rules the violation or fulfillment of a condition is not bound to an action. Here, choosing an action to solve a problem is the result of a synthesis of conditions (Ruas and Plazanet 1996, Barrault *et al.* 2001). But constraints are not only useful to decide on the generalization algorithm to apply if several requirements have to be considered. Their primary role is simply to *evaluate* whether the requirements on the map, a situation, or a single map object are fulfilled or not.

The requirements for map generalization that are identified in Section 2.1.3 can be formalized by means of constraints. Thereby, the different types of requirements listed (i.e. geometrical, topological, structural, etc.) correspond to similar types of constraints mentioned in the generalization literature (e.g. Weibel and Dutton 1998). In Research Paper 3 we give examples for geometrical requirements expressed as constraints.

2.2.3. Constraint-based Automated Map Generalization using Workflow Systems, Multi Agent Systems and Optimization

The introduction of constraint-based modeling did not only enable new approaches to automated map generalization, such as agent modeling, but also enabled the integration of interactive and rule-based methods in a more sophisticated way by workflow systems. *Workflow modeling*, and flowchart modeling respectively, is a technique often used by so-called data flow visualization systems (e.g. the Application Visualization System by Upson *et al.* 1989), exemplified in the GIS domain by ESRI's ModelBuilder ®[4].

Workflow models provide an intuitive way of chaining together several processing tasks (e.g. building elimination, simplification, displacement, etc.), whereby the final order of the tasks is interactively defined by an expert (see Figure 2.4). Thus, rules can be executed in a dynamic order in contrast to batch systems that execute rules in a fixed order. Constraints can be used in the workflow approach to characterize the map in a first step. In the second step, based on the characterization results, map partitions[5], themes and map objects can be assigned different processing paths that have been setup interactively as a workflow. An example for a constraint- and workflow-based generalization system has been presented in Petzold *et al.* (2006).

The *Multi Agent System* developed during the AGENT project (Barrault *et al.* 2001) is a further approach to automated map generalization that utilizes constraints. The system follows the conceptual generalization model presented by Ruas and Plazanet (1996). Every map object is represented by a so-called *agent* object that knows the constraints that apply to it. While agents representing individual map objects (e.g. a building) are termed micro-agents, these agents can be

[4] ArcGIS 9.2 Desktop Help - An overview of ModelBuilder:
http://webhelp.esri.com/arcgisdesktop/9.2/index.cfm?TopicName=An_overview_of_ModelBuilder

[5] A map partition denotes an area of the map that is generalized independently from other map areas. For instance major roads and rivers, or available town boundaries, can be used to derive a partitioning of the map space (Timpf 1998, Gaffuri and Trévisan 2004).

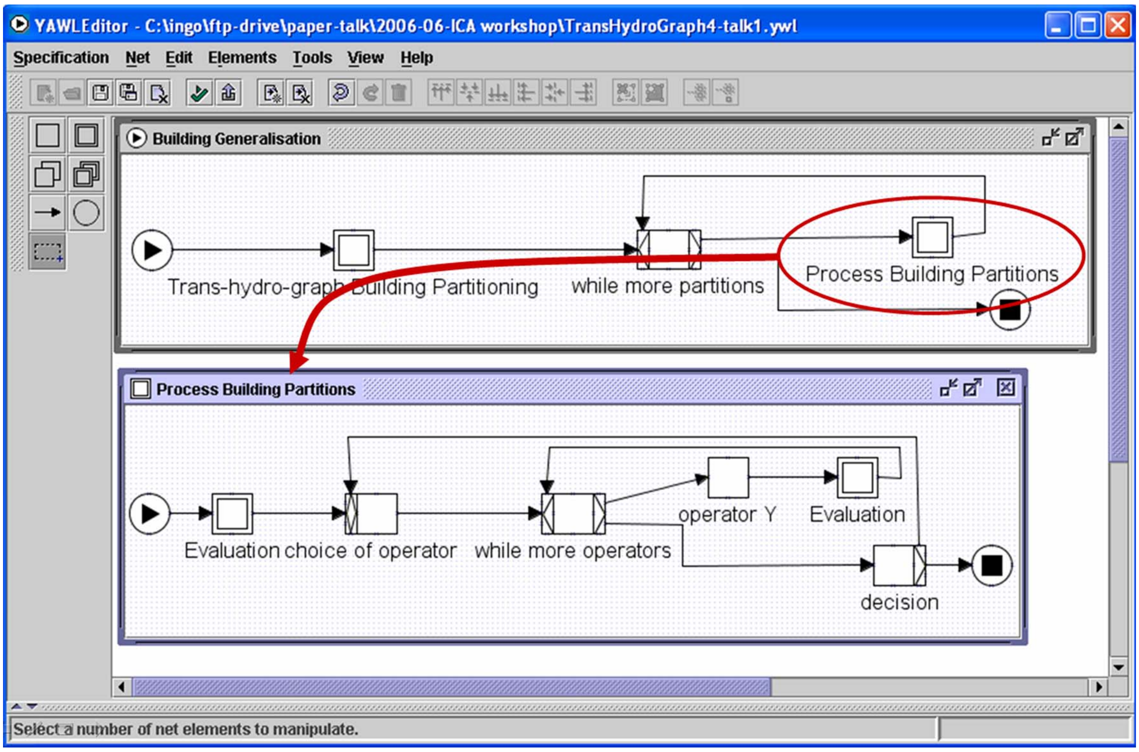


Figure 2.4.: An example for workflow modeling in map generalization from Petzold *et al.* (2006).

managed by so-called meso-agents that represent groups of map objects (e.g. the buildings of a city block). All agent objects carry out a self-evaluation, using the constraints, and apply the appropriate generalization algorithms if a constraint is not satisfied. Two different approaches for agent modeling have been proposed for map generalization. In the original approach by Ruas (1999) a strictly hierarchical model of macro[6], meso, and micro object agents were employed, where communication is restricted to a top-down process. Communication is necessary for instance if objects within a group need to be selectively deleted, or displaced from each other. In the second agent modeling approach proposed by Duchêne (2004), the communication is accomplished non-hierarchically between the single-object agents. Research Paper 3 describes how the agent model by Ruas (1999) was used to generalize buildings independently from each other, but in this case without using communication. A detailed introduction to the two agent-based generalization models and their application is given by Ruas and Duchêne (2007).

Several *optimization* based approaches to map generalization are described in the literature (Harrie and Weibel 2007). It is useful to distinguish three types of optimization approaches:

- combinatorial optimization (Michalewicz and Fogel 2004),
- continuous optimization (Boyd and Vandenberghe 2004), and
- neural networks (Bishop 1995).

In optimization approaches a problem is formulated in terms of an objective function and one or several minima or maxima values of that function are sought. A simple approach to define an

[6]In the AGENT prototype a macro level agent is used to monitor the lower levels. The macro agent transmits user requirements by setting up the constraints of the top-level meso agents and afterwards triggers their life-cycles (Barrault *et al.* 2001).

objective function for map generalization is to evaluate the violation/satisfaction of the constraints, obtaining either Boolean or continuous results in the interval [0..1], and calculate their weighted sum. In the following we aim to give a short overview of the optimization approaches used for map generalization. Duda *et al.* (2000) describe several of the optimization techniques typically used, except snakes and finite elements.

Combinatorial optimization techniques such as simulated annealing or genetic algorithms try to find iteratively an optimal solution. Thereby the process of finding an extreme is influenced by a stochastic component (e.g. flipping a coin) when intermediate solutions of one iteration step are evaluated as being good or bad. Generalization approaches based on genetic algorithms have been presented by Neun (2007) for the generalization of a building block using several cartographic operations, and by Wilson *et al.* (2003) for the displacement of buildings. Simulated Annealing strategies for the generalization of buildings are presented by Ware and Jones (1998), Ware *et al.* (2003) and Neun (2007).

Continuous optimization techniques require a continuous and differentiable objective function. The advantage of such methods is that a generalization solution can be achieved in one step. But iterative approaches are possible as well. Several continuous optimization approaches have been used in the past. For instance Steiniger and Meier (2004), Bader (2001), and Burghardt (2005) present approaches for line smoothing and line displacement based on the snakes method and on the technique of elastic beams (Bader 2001). An optimization by least squares adjustment has been applied by Sester (2000a), and Harrie and Sarjakoski (2002) to generalize buildings. Harrie and Sarjakoski (2002) also include roads and other polygonal objects in the process. Finally a further approach based on the Finite Element Method for the simultaneous displacement of buildings has been presented by Højholt (2000).

Neural Networks deliver an optimal solution if they are trained for the specific problem. Up to now they have not been used for modeling entire generalization processes but for the realization of specific generalization operations. For instance Højholt (1995) as well as Sester (2005) use a specific type of neuronal network, a self organizing map - SOM (Kohonen 2001), to generalize buildings with the condition that the settlement structure must be preserved (i.e. cartographic typification). A further application has been reported by Jiang and Harrie (2004) for the selection (omission) of roads in a network.

From above presented approaches only workflow modeling and agent modeling have been used to model the entire generalization process. Although it is not impossible that the other approaches can be used to model the entire process, a clear advantage of workflow and agent based techniques is that other kinds of multi condition solution processes can easily be incorporated, such as rule-based and optimization techniques.

3. State of the Art in Spatial Pattern Analysis and Emerging Research Challenges

In this chapter we review the literature on spatial pattern analysis. Thereby we commence by investigating spatial pattern analysis in related disciplines, such as geography and landscape ecology. We then move on to the literature covering data enrichment for map generalization. The chapter is concluded by outlining the research challenges with respect to this thesis.

3.1. Spatial Pattern Analysis in Related Disciplines

A survey of the literature on the analysis of relations and patterns in geographic data reveals a very broad interest in this topic by several disciplines outside of cartography. We will give an overview of publications in three geography related disciplines that provide a useful source of pattern analysis techniques with respect to our research objectives. Additionally we consider psychology, since cartography is not only interested in patterns of semantic meaning, but also patterns that are mentally formed.

Geography - The exploration and analysis of spatial structures is one of the fundamental questions of geography. The analysis of spatial configurations, e.g. the search for patterns, serves on the one hand the construction of new models of human interaction with the environment, and is used on the other hand to validate existing models. For instance the geographical analysis of the spread of diseases, comparison of economic situations, and observations of technology adaptation have led to the development of general and subject specific spatial diffusion models (Haggett 2001). In particular the analysis of point patterns (Haggett *et al.* 1977, O'Sullivan and Unwin 2002) with respect to distribution density and regularity has been applied to such different topics of geography as settlement analysis, spatial arrangement of stores, or geographical epidemiology (Gatrell *et al.* 1996). Not only point configurations but also spatial autocorrelation between spatial units and patterns in networks have been of interest to geographers (O'Sullivan and Unwin 2002). For instance Garrisson and Marble (1962, in Haggett *et al.* 1977) analyzed flight networks in the early days of computing to discover principal flight connections in Venezuela.

Urban Modeling and Planning - Studies in urban modeling are concerned with the analysis of urban building and road structures. The objective of urban modeling is to develop an understanding of physical and socio-economic distributions by studying and modeling urban process and structures (Longley and Mesev 2000). The emergent models can be used in socio-economic analysis and urban planning. Work concerned with urban pattern analysis has been carried out for instance by Barr *et al.* (2004). They verify a mapping between urban form and function by evaluating the separability of building patterns of different architectural epochs. Junior and Filho (2005) apply multi-scale lacunarity (i.e. degree of 'gappiness') measurements to characterize neighborhoods within a Brazilian town. Furthermore the analysis of street networks in terms of so-called space syntax (Hillier and Hanson 1984, Jiang and Claramunt 2002) and centrality (Porta *et al.* 2006, Boccaletti *et al.* 2006) has been of interest in urban modeling. Such an integration and centrality analysis requires network maps. Approaches to derive such network maps, called axial maps, are presented by Carvalho and Batty (2004) and Batty and Rana (2004). Thereby the axial map consists of axial lines that correspond to lines of sight within an urban area. Also worth mentioning, though not directly belonging to urban modeling, is the book by Marshall (2005) who discusses urban (street) patterns from a transport planning perspective and also recalls several urban pattern classifications of the past century.

Landscape Ecology - Most of the studies mentioned above concentrate on the description of the human made environment or patterns related to human-environment interaction. In contrast, landscape ecology aims to characterize structures and patterns in the natural environment. For instance McGarigal (2002) distinguishes four types of patterns for the characterization of landscapes:

1. spatial point patterns (e.g., randomly or clustered distribution of trees in a forest stand),
2. linear network patterns (e.g., different types of river networks),
3. surface patterns (e.g., density distributions of individuals), and
4. categorical patterns (e.g., landcover configurations).

Algorithms for the recognition of landscape related patterns are usually developed for the analysis of raster or image data, in contrast to vector data used in this thesis. The characterization of landscapes has addressed diverse topics such as the complexity of landscape boundaries (Metzger and Muller 1996), landcover classification and change (e.g. forest succession: Hall *et al.* 1991), and species composition (e.g., forest species: Martin *et al.* 1998). A particularly interesting attempt at pattern preservation is the well developed set of landscape metrics to evaluate landscape diversity and its spatial configuration (Gustafson 1998, McGarigal and Marks 1995). We believe that these environmental pattern indices will be useful in map generalization to evaluate whether natural patterns are preserved. An application of landscape indices to the semi-automated generalization of a soil map has been shown by Fuchs (2002).

Psychology (psychology of art, perception[1] and cognition[2]) - There are certain fields of psychology that are not directly concerned with spatial patterns, but nevertheless are interested in the spatial configurations of objects that create mental patterns. Most notable for cartography is the literature on Gestalt psychology which describes the conditions that form perceptual patterns and visually attracting configurations (Koffka 1935/1955). Especially the work of Wertheimer (1923/1938) describing the *laws of organization in perceptual form* can help to identify (geometric) patterns that are perceived by the map reader, and that should be preserved during map generalization. Another work that describes visual attracting configurations is Arnheim's (1954/2004) *Art and Perception*. Although this book is primarily dedicated to students of the arts, it provides together with his book *Visual Thinking* (Arnheim 1969/2004) valuable insights into perceptual and cognitive processes when a human observes sculptures, graphics and paintings. A similarly interesting source

[1]Perception: In psychology and the cognitive sciences, perception is the process of acquiring, interpreting, selecting, and organizing sensory information. (see Gleitman *et al.* 1999)

[2]Cognition: Includes all the mental processes that are used to obtain knowledge or to become aware of the environment. Cognition encompasses perception, imagination, judgment, memory, and language. It includes the processes people use to think, decide, and learn. (see Gleitman *et al.* 1999)

for cartographers has been Bertin's book (Bertin 1967/1983) that focuses on design guidelines for (thematic) maps and illustrations. Whereas the five mentioned references are comparatively old, but nevertheless seminal publications, the text book by Palmer (1999) and the article by Scholl (2001) provide a more recent review of research on objects and how they stimulate (visual) attention.

3.2. Spatial Pattern Analysis and Data Enrichment in Map Generalization

In automated map generalization, pattern recognition and analysis is gaining increased attention by researchers. Cartographic pattern analysis is usually carried out on vector data (e.g. line drawings). In the following paragraphs we will review the developments, organized in the first instance by topographic and thematic maps. Due to the diversity of publications on topographic maps, we will further address the developments separately for the thematic and geometric components of topographic maps. A further distinction is made into approaches that analyze building configurations, polygon configurations, networks and individual lines.

3.2.1. Topographic Maps

Analysis of Building Configurations

A fair amount of publications consider the extraction of urban patterns and distinct configurations based on the analysis of buildings or building parts. In order to organize these publications, we will address articles that consider large geographical patterns first, then subsequently address the more detailed scales, and finally discuss publications that cannot be related to a particular scale.

Large Building Patterns - At least three research groups have been working on the detection of large building groups (i.e. at town level). In the work presented by Chaudhry and Mackaness (2006a) the outlines of settlements (e.g. city borders) are identified using a gravity-based polygon buffering approach. Thereby for every building a gravity coefficient is calculated and subsequently used to decide whether a building is contracted or expanded by buffering. A final step unifies the buffers to deliver a polygon that covers the settlement area. In an earlier piece of research Boffet (2001) developed a buffer based approach to detect and distinguish urban settlements into towns, villages and hamlets. She does not use a gravity coefficient to decide on the dimension of the buffer-radius, and instead she identifies appropriate buffer radii empirically. A classification into settlement types is accomplished by analyzing the area size of the unified building buffers. The approach used by Revell (2004) and Revell *et al.* (2005, 2006) to identify urban and rural areas is very similar to the method presented by Boffet (2001). Additionally they utilize the classification by activating different building generalization algorithms according to the urban or rural context.

Medium Size Building Patterns - Techniques discussed in this paragraph focus on the identification and classification of medium-sized building groups (e.g. urban blocks). A method developed by Boffet (2000) aims at classifying different types of urban zones (e.g. scattered blocks, dense residential, industrial, etc.). The approach is based on the analysis of functional (attribute) and gestalt (geometric) properties of buildings within a building block which is surrounded by streets.

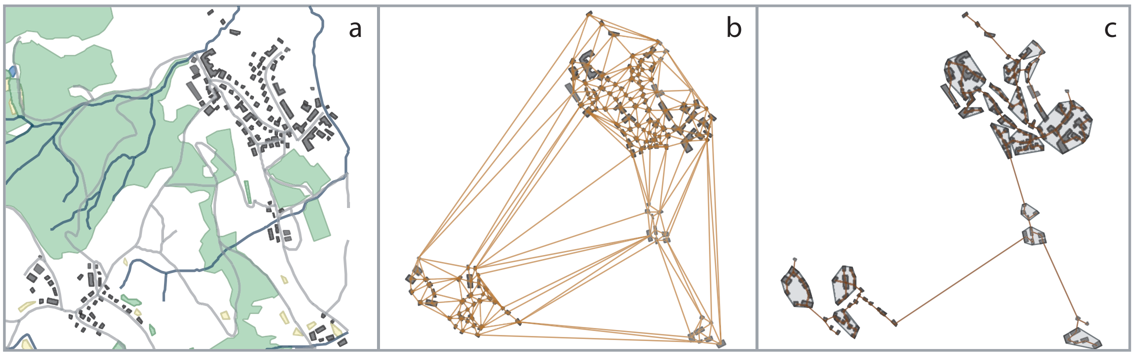


Figure 3.1.: Grouping of buildings: a) original map, b) Delaunay triangulation of buildings, c) Minimum Spanning Tree of buildings and detected smaller groups. (simulated data)

An approach presented by Regnauld (1996, 2001) focuses on the detection of perceptual 'natural', i.e. homogeneous, building groups. The buildings are connected first using a proximity graph and afterwards the graph is analyzed and segmented, resulting in building groups (see Figure 3.1c). The method is used to preserve similarities and differences between the building groups with respect to density, size and orientation of the buildings during building typification. The proximity graph algorithms are presented in detail in Regnauld (2005).

A further graph-based approach to detect such 'natural' building groups has been presented by Anders (2003) and Anders *et al.* (1999). In contrast to Regnauld (2001), a clustering technique is used to identify and remove graph edges in order to establish homogeneous building groups. The approach presented recently by Anders (2006) focuses on the detection and typification of grid like building arrangements, rather than arbitrary shaped groups. The building grouping technique developed by Bard (2004) is very similar to the clustering based method of Anders (2003). Bard's approach is based on the multi-level spatial cluster analysis developed by Estivill-Castro and Lee (2002). The objective of a paper by Allouche and Moulin (2005) is to acquire dense urban building areas and replace them by bounding polygons. The detection of dense areas is accomplished by utilizing a neuronal network, i.e. a self organizing map (SOM, Kohonen 2001). Finally, Li *et al.* (2004) present a method to detect (larger) groups of buildings as inputs to typification and amalgamation operations. They first form small groups by analyzing neighboring buildings in terms of distance as well as similarity in size, shape and orientation. Afterwards they merge adjacent groups of same type to larger groups according to a distance criterion. For the neighborhood analysis Li *et al.* (2004) employ a Delaunay triangulation (see Figure 3.1b) and its dual, the Voronoi regions.

Small Buildings Groups - The techniques by Regnauld (2005) and Li *et al.* (2004), for the detection of medium-sized building groups use the road network as an additional input for the generation of groups. This also holds for most of the approaches that have been developed to identify small buildings groups, e.g. building alignments. The consideration of road data as an additional input is beneficial when the detection of building alignments is seen as a local spatial problem. By assuming that such alignments exist only within a building block surrounded by roads, the computational burden can be reduced by first partitioning the data using a road network. Boffet and Rocca-Serra (2001), for instance, identify meaningful building alignments, i.e. building triplets, within one urban block. Thereby adjacent buildings are seen as a meaningful group if they are homogeneous in orientation and area, and are separated by similar distances. Apart from the identification of building groups, the paper by Boffet and Rocca-Serra (2001) also presents a buffer-based method to calculate building-free spaces (i.e. the 'white space' of the map). Such information can, for instance, be used to control displacement operations.

A further approach to detect building alignments is proposed by Christophe and Ruas (2002). They call the method "straight line assessment", since the centroids of buildings are projected on a plane which is moved by 1 degree increments around the building block. If at least three projected centroids fall together, then an alignment may be identified. In a subsequent paper by Ruas and Holzapfel (2003) these detected alignments are characterized to identify significant groups that should be maintained during the generalization process. An application of the structures identified by Boffet (2001), Bard (2004), Boffet and Rocca-Serra (2001), and Christophe and Ruas (2002), i.e. towns, urban block classification, white space and alignments, is given by Gaffuri and Trévisan (2004). They select different generalization operations depending on the type of building group detected.

A simple but effective method for building alignment detection has been published by Burghardt and Steiniger (2005). The buildings are grouped if they are within a certain distance from a street and on the same side of the street. Afterwards a homogeneity coefficient is calculated for every group with respect to similarity in building size, shape, orientation, and building distances, which is used to identify meaningful groups.

Characterization of Individual Buildings - A classification of individual rural buildings is proposed by Rainsford and Mackaness (2002). By analyzing the sequence of building wall turns (i.e. left and right turns) they match buildings to the shape of the single letters: I, F, P, G, E, L, U, O, T. In the generalization process this information is then used to replace the original building by a building template that has a simplified shape similar to the matched letter. A classification of buildings is also presented by Mustière *et al.* (2000). They characterize buildings using several shape measures and establish generalization rules. These rules are based on the characterization results and help to select appropriate generalization operations for buildings depending on their character. The rules are established by utilization of machine learning algorithms such as C4.5 (Quinlan 1993), which is used to create a decision tree leading to a qualitative description of a building. Following this step, a second learning algorithm is used (ENIGME by Ganascia *et al.* 1993) to learn rules for applying the generalization operations. The work by Mustière *et al.* (2000) builds on previous work by Regnauld *et al.* (1999). They propose a classification of buildings based on two geometric properties (size: big/small, and shape complexity: simple/complex) and develop different generalization algorithms. The algorithms are the ones that are triggered by the rules of Mustière *et al.* (2000). Regnauld *et al.* (1999) not only suggest building characterization by size and shape, but also identify different building wall configurations that should be considered by the algorithms. For instance they distinguish between hat and stair wall configurations as well as wall-wall and corner-wall distance conflicts. Finally Sester (2005) and Burghardt *et al.* (2005a) also detect and utilize different building wall configurations to enable an appropriate building outline simplification.

Other Types of Building Data Enrichment - The approaches presented in the paragraph of this section do not aim to establish building groups but rather involve methods to characterize the configuration of buildings. For example Basaraner and Selcuk (2004) calculate Voronoi polygons from individually generalized buildings that are partitioned according to the building blocks. In a later step the density of Voronoi polygons within a block is evaluated to decide which building generalization algorithm (e.g. amalgamation, displacement) to choose next. Ai and van Oosterom (2002a) also generate and use a data structure that is similar to a Voronoi diagram. By a neighborhood analysis that utilizes a Voronoi-like structure, building displacement forces are propagated differently across the building block. The third paper by Bader *et al.* (2005) does not utilize Voronoi regions but utilizes a graph structure, the minimum spanning tree (MST, Regnauld 2001). They create a so-called ductile truss from the MST, where every edge of the truss connects two building centroids. These truss edges are then weighted by the distance and parallelism of the two adjacent buildings. The weighting enables a building displacement that accounts for the spatial relations between the buildings and hence allows the particular spatial arrangement to be preserved. A weighting of connecting edges between buildings is also proposed by Burghardt and Cecconi (2007) for building typification operations. Their algorithm generates a Delaunay triangulation of the buildings, and the edges are weighted by the local building density and the size, shape, and orientation of the two adjacent buildings. Here the edges with low weights are removed first and the two adjacent buildings are substituted by a placeholder building located at the midpoint.

Analysis of Polygon Configurations

There have been only few attempts to study data enrichment for the generalization of non-building polygons such as lakes, islands and forest areas. The assumption is that many or most of the methods mentioned for the detection of building groups are applicable to such non-building polygons as well. This has been demonstrated for instance by Chaudhry and Mackaness (2006a) who adapt the gravity-based algorithm described previously, for the generalization of forest areas and lakes. The gravity approach builds on the *rich get richer and poor get poorer* principle that has been employed previously by Müller and Wang (1992). They rank the objects (area patches such as lakes and islands) according to their area, to decide whether an object is enlarged or contracted. Area patches that are too small are eliminated or randomly reselected, and enlarged patches that overlap are merged. The book by Bertin (1983) also discusses an example of lake generalization and inspired both previous works. However, Bertin (1983) describes only the steps that are executed manually by a cartographer to generalize a group of lakes appropriately. No approaches have been reported that automate Bertin's steps of structure recognition and generalization comprehensively.

To support the generalization of islands Peng *et al.* (1995) develop an approach for the detection of "regular-linear distributed" islands, i.e. an island alignment. The approach is based on the analysis of triangles in a Delaunay triangulation constructed from the island centroids. Peng (1997) also presents a safe region concept for a single polygonal object, in this case applied to buildings. The safe region demarcates a zone in which a polygon can be enlarged or displaced without generating conflicts with neighboring polygons. Such regions are also generated from a Delaunay triangulation. A specific data structure that is applicable to the generalization of non-building polygons, networks, lines and contours is presented by Gold (1999) and Gold and Thibault (2001). The so-called quad-edge structure is based on the Voronoi diagram and can be used to derive a skeleton from a polygon. If the branches of the skeleton are pruned/retracted, then one obtains a simplified version of the object, i.e. a simplified polygon.

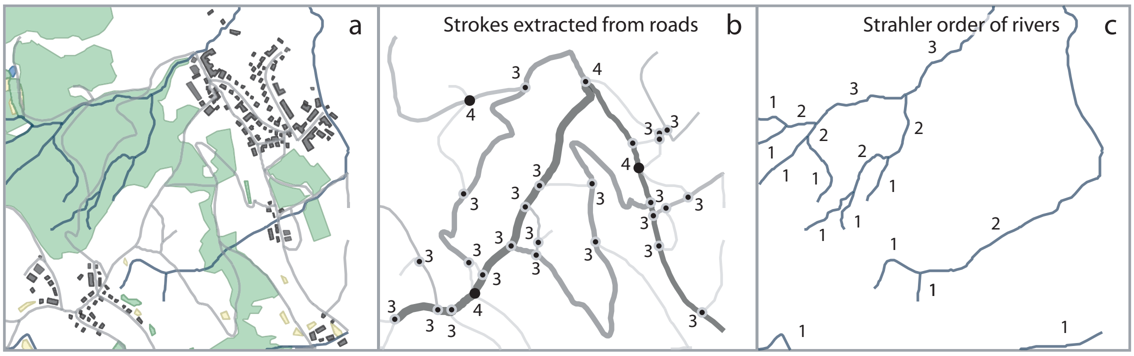


Figure 3.2.: Network analysis: a) original map, b) road network analysis by connectivity of junctions and strokes formation (the darker and the heavier the lines, the more important the stroke), c) river network and Strahler ordering, the preceding step to obtain the Horton ordering of river segments. (simulated data)

Analysis of Networks

If networks (e.g. road and river networks) are to be generalized, then the most prominent properties to preserve are the network density and the network connectivity. Whereas the first property is quite a perceptually important property, the preservation of the connectivity plays an important role for the intended map use. For instance if the connectivity in a road map is lost, then a car driver may choose an unnecessary detour. The principal question of network generalization is: "Which roads/rivers of the networks are important and have to be retained?"

A first attempt to answer this question for road networks was presented by Mackaness and Beard (1993) who proposed a graph theoretical analysis of road networks. More specifically they suggested ranking streets based on their remoteness, their richness of connections to other cities, and their uniqueness in connecting two cities. Two years later Mackaness (1995a) proposed for urban areas the extraction of urban axial lines, i.e. urban lines of sight, and the use of alpha analysis measures, such as connectivity, depth, and control, to support cartographic generalization. This proposal is related to the literature on space syntax discussed in Section 3.1. Mackaness (1995a) also points out, however, that tests with acyclic river deltas and railway networks were disappointing. But he suggests that it should be useful to merge the axial (metrical) representation and graph (topological) representation. Richardson and Thomson (1996) and Thomson and Richardson (1999) finally integrate thematic, topological and metrical information to generalize road networks. In Thomson and Richardson (1999) they propose a utilization of the Gestalt principle of *good continuation* to create so-called *strokes*; a line structure that chains together several visually continuous road segments (see Figure 3.2b). Strokes are considered to be a basic pattern of the road network that must be preserved. The importance of one stroke within the network can be estimated from their length and connectivity property. Thomson and Brooks (2000, 2002) later refined the approach and adapted the technique for the generalization of river networks. The refinement of the technique for road networks has concentrated on the calculation of the importance value of a stroke. For river networks strokes are used to define the main path of a river. The weighting of the river strokes should reflect the hierarchic organization of a river network, therefore Thomson and Brooks (2002) use the Strahler/Horton ordering scheme (see Figure 3.2c).

Two other approaches to obtain a weighting for road segments are presented by Morisset and

Ruas (1997) and Jiang and Harrie (2004). Morisset and Ruas (1997)) derive the importance of a road from simulating the movement of cars on the road network. The more traffic there is on the road, the higher the importance. Jiang and Harrie (2004) utilize a self organizing map (SOM) to identify which streets are more important than others. They describe every street by topological parameters that are partly obtained from a network analysis, such as node degree, closeness, and between-ness, but also by metrical properties (road length) and attribute values (e.g. lanes, speed, class). Heinzle *et al.* (2005, 2006) focus not on the importance of every road in the network, but rather on the identification of specific network patterns. They distinguish and extract star-shaped, grid-like, and ring-shaped road patterns. Zhang (2004a) also describes these types of network patterns but does not develop methods for their detection. Rather he concentrates in (Zhang 2004b) on the preservation of density differences in the road network. He applies strokes and performs a connectivity analysis of the junctions. Preserving density differences is also the objective of methods proposed by Edwardes and Regnauld (2000) and Edwardes and Mackaness (2000, accepted). They classify the road network in inner cities, urban areas and rural areas. This abstract information on network density together with the stroke model is subsequently used to remove streets by aggregating urban blocks.

Two papers discuss the analysis of networks to support the automated generalization of Ordnance Survey maps. In the first paper by Revell *et al.* (2006) the steps for adaptive generalization of a river network are described. The river segments are classified into four width classes and additionally described by their Horton stream order. This information is then used to trigger the appropriate generalization operations and prune the network as described by Thomson and Brooks (2000). The second work by Thom (2006) addresses the identification and classification of distance conflicts within a road network. A further study that aims to extract information to guide the generalization of river networks was published by Ai *et al.* (2006). They build a hierarchical watershed partitioning model from a Delaunay triangulation and determine the importance of a river segment with respect to the area of the contributing watershed. Ai *et al.* (2006) justify the chosen selection approach by the distinct relationship between watershed area and river network parameters such as river density, network order (e.g. Horton order) and channel length.

The last two publications that we would like to consider in this sub-section, deal with road network simplification in terms of model generalization. Hence, they do not focus on a visually appealing output. Mackaness and Mackechnie (1999) describe an approach to simplify road junctions in road network datasets. A clustering algorithm is used to identify the junctions that will be potentially merged into one and a network graph is established. Then the junctions are simplified by calculating a new centroid and using information from the graph to connect the new point to the network. The second approach by Petzold *et al.* (2005) aims to extract a topological consistent road network represented by lines, from a polygonal representation of roads. Such a polygonal presentation usually exists in large scale city plans. To extract the network Petzold *et al.* (2005) establish a polygon connectivity graph and a skeleton graph. The graphs are used to decide how polygons are merged to obtain a topologically correct and consistent network representation.

Analysis of Lines

The publications presented in the previous sub-section address data enrichment for the generalization of complete networks. In this sub-section the focus will be on data enrichment for the generalization of network segments, e.g. road or river segments that are part of a larger network. The necessity for an adaptive approach to line generalization has been highlighted by Plazanet *et al.* (1995). They show for instance how a line is generalized differently in manual cartography depending on its context. They further demonstrate the insufficiency of simple line simplification algorithms (e.g. the Douglas-Peucker algorithm, Douglas and Peucker 1973) to handle complex situations, such as hairpin bends of mountain roads. Their approach presented in Plazanet *et al.* (1998) to overcome these problems is based on recursive line segmentation in homogeneous parts. The segmentation is performed on detected inflection points. Apart from the segmentation they also classify the segments into four classes that correspond to different line sinuosity by employing a k-means clustering. This information is then used in machine learning algorithms to determine rules on the generalization operation to apply, such as bend elimination, shape emphasis and smoothing (see also Ruas and Plazanet 1996).

A similar study that employs machine learning techniques for road generalization is reported by Lagrange *et al.* (2000). They use a neuronal network to determine parameters for road smoothing, based on road segment characterization with 10 geometric measures. Finally Mustière (2005) integrates all previous mentioned studies on road classification and knowledge acquisition with machine learning techniques performed at the COGIT lab. He establishes a comprehensive road generalization system that enables adaptive generalization utilizing diverse generalization algorithms. The application of these road generalization methods in map production for the French topographic map TOP100 is presented in Lecordix *et al.* (2005).

The strategy of the previously mentioned approaches to road generalization has been to subdivide the line and generalize its parts with a multitude of algorithms. In contrast, several authors present a line generalization approach based on the *snakes* model, where an adaptive generalization can be realized by a context-dependent choice of parameters. A smoothing approach with snakes is presented by Burghardt (2005). To obtain a different degree of smoothness on the portions of a line, he segments the line based on its sinuosity. Following that he smooths the elements separately with constant snakes parameters. Steiniger and Meier (2004) propose a snakes approach that employs two possibilities for an adaptive smoothing. On the one hand they use segmentation to preserve salient points, and on the other hand they control the degree of smoothness by an estimation of the local curvature (Figure 3.3). The snakes approach by Guilbert and Lin (2006) addresses the specific problems when bathymetric contours require smoothing for marine charts. They identify critical points that need to be retained by using the Douglas-Peucker algorithm. Furthermore, they analyze the local situation and parameterize the snake in such a way that the bathymetric line cannot move towards the shallow water (a safety constraint).

An approach to line generalization based on snakes and elastic beams, respectively, has been proposed by Bader (2001). In contrast to the studies cited above, his work focuses not on line simplification, but on line displacement within a road network. To enable sufficient generalization, different situations need to be detected to appropriately parameterize the snakes and beams. For instance, the network must be analyzed to propagate road displacement across road junctions and to enable displacement of road junctions themselves. Additionally (a) junctions are characterized to support perceptibility of incoming road orientation, (b) narrow bends are identified to avoid their further compression, (c) straight road elements are detected to allow their shrinking if space is needed to enlarge bends, and (d) the stiffness of roads is parameterized according to road class. Similar to Bader (2001) snakes displacement has been employed by Burghardt (2001)

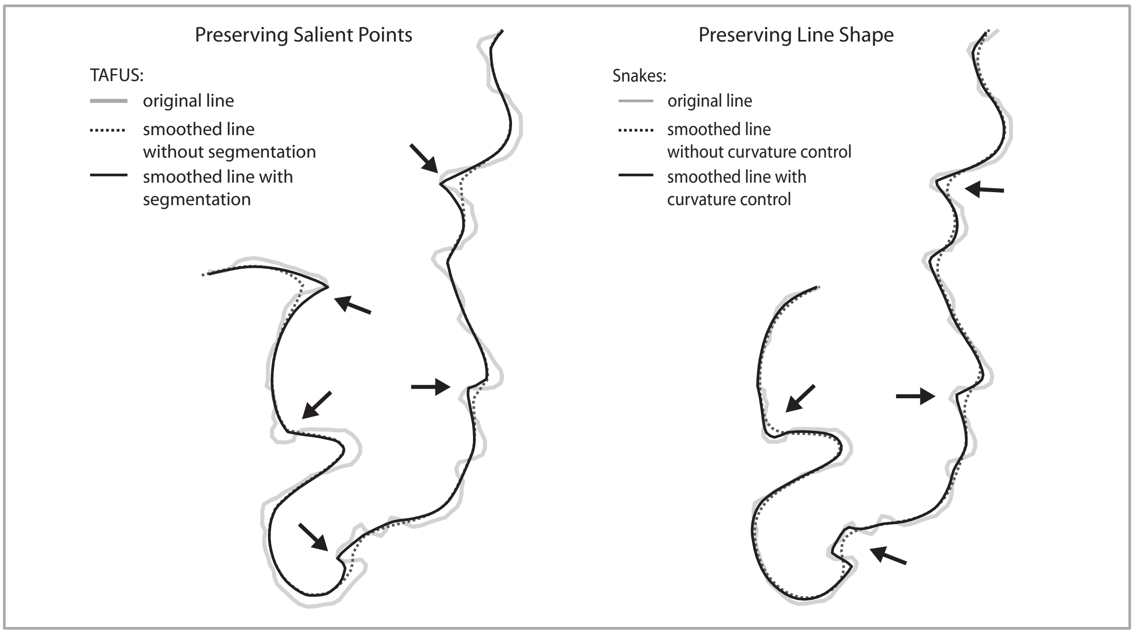


Figure 3.3.: Improving line smoothing by informed snakes/TAFUS algorithm application: segmentation at salient points and curvature controlled smoothing (taken from Steiniger and Meier 2004).

and Guilbert *et al.* (2006). Burghardt (2001) freezes junctions with an additional parameter, and different types of roads can be displaced differently. For the displacement of bathymetric contours presented by Guilbert *et al.* (2006) the safety constraints, which avoid contour movements towards shallower areas, and the shape preservation constraint require a preceding analysis. Here, the shape preservation is ensured by applying different parameter settings to curves.

The work by van der Poorten and Jones (2002) on line analysis can be seen as a special case of the divide-and-conquer generalization strategy, since it enables the development of a customized set of generalization algorithms. In the first step of the approach a Delaunay triangulation for a single line is established and analyzed to identify bends, or branches respectively. In the second step the identified bends are characterized by several measures that allow generalization operations to be guided, such as global smoothing and individual bend removal. Two further works should be mentioned that deal with analysis and generalization of lines. Nakos and Mitropoulos (2005) review existing methods for the detection of ”critical points” to be retained during line simplification. Aside they propose their own critical point detection approach. Wang and Müller (1998) present a prototype system that generalizes lines according to the results of a preceding bend analysis. The bends are assessed in terms of size, shape, isolation and similarity.

The generalization of *contour lines* demands specific analysis approaches that are different from the ones used for 2-D features such as roads. This is due to the fact that contours represent continuous relief rather than discrete objects. Thus contour generalization must not only account for a visually appealing result, but also for constraints that emerge from possible further contour-based spatial analysis and (human) interpretation. Two principal methods exist to generalize contours. The first approach is to generalize or smooth the digital terrain model and calculate the new, generalized contours from it (Weibel 1992). In the second approach the contour lines themselves are generalized. To enable a sufficient generalization both approaches require a preceding terrain analysis to detect ridges and channels (Weibel 1992, Werner 1988). For a review of contour generalization we refer to Weibel (1997) and the book on terrain modeling by Li *et al.* (2005).

In the above literature review of data enrichment for topographic map generalization, it appears that *graph structures*, such as the Delaunay triangulation, receive ample attention. They enable individual lines to be analyzed but also help to identify and represent the spatial configurations of several objects in terms of geometry and topology. Therefore graph structures and topological intersection models (such as the DE-9IM model specified by the Open Geospatial Consortium[3], see OGC and Chair 1999) can be seen together as essential components of data enrichment. This has been shown for instance by Neun *et al.* (accepted) who outline the utility of graph structures for map generalization web services. With respect to the utility of graph structures for map generalization we would finally like to mention the papers by DeLucia and Black (1987) and Jones *et al.* (1995). They were among the first to utilize the Delaunay triangulation for different polygon generalization operations and hence demonstrated the feasibility of contextual generalization operations, such as amalgamation and displacement, with vector data.

3.2.2. Thematic Maps

In contrast to the existing literature on the generalization of topographic maps, little research has been carried out on automated generalization of categorical maps, including associated pattern detection and data enrichment procedures. Therefore we will not restrict the review to methods that search for a specific pattern or aim to classify situations, but rather consider work on data enrichment for thematic maps in general. One of the examples where a spatial analysis is performed to control a subsequent generalization process is presented by Fuchs (2002). For the derivation of soil maps of 1:100 000 and 1:200 000 scale from 1:50 000 scale, he develops a number of tools that should support the soil scientist's decisions for the semantic aggregation of soil types. The tools proposed by Fuchs (2002) enable the soil scientist to identify composition patterns in the soil landscape. Thus Fuchs identifies geometric and statistical *measures* that help to describe the composition of *map units*[4] and map situations. Other authors that have proposed measures to quantify the content of categorical maps include Peter (2001), Fairbairn (2006), Li and Huang (2002), Cheng and Li (2006) and Bregt and Bulens (1996).

One of the objectives of Fuchs (2002) has been to derive an *aggregation schema* to reduce the number of soil types in the soil map. He uses a cluster analysis to identify similar soil types that can be grouped. In contrast to Fuchs (2002), van Smaalen (2003) developed a class-adjacency index due to a lack of descriptive attributes for the original classes. Based on this index he subsequently derives an *Object Aggregation Factor* that determines whether neighboring areas can be aggregated. A different approach for identifying which polygons to merge is proposed by Haunert and Wolff (2006). They assume that an aggregation schema for categories exists. The method utilizes a linear optimization approach, i.e. mixed integer programming, which can account for different constraints to respect cartographic principles. Downs and Mackaness (2002) decide on which polygons to merge in a geological map, based on the class (e.g. similar category) and on the

[3]Open Geospatial Consortium: http://www.opengeospatial.org

[4]In soil sciences a *map unit* denotes a particular soil type or a compound of soils that is referenced as a category in the map legend (see Rossiter 2000). In cartography *map unit* corresponds to the unit used to measure map coordinates (e.g. meters).

geometry (e.g. size) of neighboring polygons. Special attention is paid to the detection and preservation of fault line patterns. Artioli *et al.* (1995) also focus on the generalization of a geological map and mention conditions for the treatment of objects in the Quaternary Period. For example they preserve landslides regardless of their size, if they are closer then 50 meters to population centers. Unfortunately it is rarely described how situations that demand a specific treatment are to be identified, since they have probably been marked manually. The approach by Atwood (2004) is also concerned with patterns that appear in categorical maps, such as geological maps. She applies a cluster analysis on type, orientation, size, and shape index values derived from polygons, to describe a dataset as being of clustered, random or dispersed structure.

A problem that appears when polygon outlines such as the boundaries of census units need to be simplified, is that the simplification algorithm should consider the nature of the boundaries involved. For instance a natural, smooth boundary imposed by a river has to be treated differently than an artificial, angular line. Therefore Galanda *et al.* (2005) modify the Visvalingam-Whyatt algorithm to preserve rectangular angles of census boundaries, which have to be detected in a preceding characterization step.

For the real-time generalization of area partitions van Oosterom (1995) developed a data structure called the GAP-tree. This tree structure has been extended by Ai and van Oosterom (2002b) to determine, by use of a skeleton partition model, how areas that are too small can be split and merged among neighboring areas, and how areas between close polygons can be bridged. Here, the applied skeleton model is calculated from a Delaunay triangulation. Earlier research by Bader and Weibel (1997) resulted in a similar approach to obtain bridge areas for aggregating disjoint polygons, but the processing was not achieved in real-time. Real-time generalization for the display of point symbols has been addressed by Edwardes *et al.* (2005) and Edwardes (2007) in a mobile information system for a nature park. The symbols, which for instance represent flower locations, have to (a) be displayed in real-time, (b) with the symbol size proportional to the number of locations, and (c) with no overlaps between the symbols. Edwardes *et al.* (2005) propose two symbol visualization methods, one based on *quad trees* (Samet 2006) and another based on hierarchical stream ordering, that respect all three conditions. Whereas the first approach accomplishes the data enrichment using a well-known data structure, the second approach requires additional elevation data to extract the hierarchical stream model, and a data structure to store the resulting partitions (watersheds) along with the associated point data.

In this section we have reviewed the map generalization literature which addresses data enrichment in some respect, either in terms of auxiliary data structures and measures for the characterization of object configurations, or in terms of information extraction. In doing so, we did not list all the references dealing with methods and algorithms for automated generalization of thematic and topographic maps. *Additional literature* that covers aspects which should be considered when characterizing maps and map object configurations can be found in Neun and Steiniger (2005) and in Research Paper 1.

3.3. Research Challenges Addressed in this Thesis

Although we did not discuss the papers of the previous sections in detail, several challenges for map generalization can be derived from this literature review. The issues that we wish to address within this thesis are highlighted below:

1) Supporting the Description of Maps and Patterns by Cataloging Relations - In the preceding section we presented a number of approaches for detecting perceptual patterns, such as alignments and building clusters, and also semantic patterns, such as urban vs. rural areas, in topographic maps. From the review an impression emerges that in most cases relations and patterns are extracted to support the generalization of one specific situation, or to inform one specific algorithm. Thus relations and patterns are classified and extracted for a specific purpose. To the author's knowledge, there are just two previous studies, namely by Mustière and Moulin (2002) and Ruas and Lagrange (1995), which have tried to establish a general inventory and classification of existing relations in maps. We deem it crucial to establish a general catalog of map relations. Such a catalog will facilitate a better description of maps and will support easier formalization of patterns of interest. Furthermore, such a catalog will point to a set of necessary pattern and relation recognition tools and algorithms, that should be available in every automated map generalization system. The development of a typology of relations, i.e. a catalog, will be addressed in Research Paper 1. The identified relations of the typology are later used to describe and extract urban structures in Research Paper 2. Finally in Research Paper 3 we demonstrate how the extracted information describing the urban structure can be used to improve the quality of the generalization result.

2) Automated Generalization of Thematic Maps - Another point that emerges from the literature review is the uneven distribution of studies devoted to topographic maps vs. those devoted to thematic maps. Of course some of the results that are obtained for topographic maps can also be applied to thematic maps. For instance geological maps often additionally contain topographic information that needs to be generalized. The challenge is that generalization systems for thematic maps must be more flexible than those for topographic maps, since the rules for displaying thematic maps may be (a) different for different map purposes (e.g. soil vs. geology), (b) the rules must be adaptable to varying semantic context, and (c) the rules should allow a certain level of fuzziness. These requirements for system flexibility emerge on the one hand from the thematic properties (e.g. soils have no crisp border but blend into one another), and on the other hand from the multitude of possible types and applications of thematic maps. To address the need for more flexibility and context-dependent mapping, it is necessary to describe the mapping data in a sufficiently flexible way, allowing generalization decisions to be made based on that description. Therefore the catalog of relations that we seek to establish, should not only consider the relations and patterns that appear in topographic maps, but also relations that appear in thematic maps. Research that addresses the description and generalization of thematic maps has been presented for instance by Peter (2001) and Galanda (2003b). These two studies are an important source of information when establishing a typology of relations that takes account of thematic map relations.

3) Description and Identification of Perceptual Patterns - Some of the above references (e.g. Regnauld 2001, Boffet and Rocca-Serra 2001, Anders 2003) aim to identify perceptual patterns such as building alignments and building clusters. However in nearly all cases these studies concentrate on the detection of building groups that are perceptually formed by spatial proximity. The first challenge that we notice is to determine whether spatial proximity principles can be applied not only to buildings but also to other geographical objects. The second challenge is to evaluate the influence of the other principles of organization in perceptual form, which have been proposed by Wertheimer (1923). For instance, if the principles by Wertheimer (1923) are capable of explaining the perceptual grouping of islands or lakes in a map, then we can utilize them for the development of perceptual group detection algorithms. We report initial results evaluating the perceptual principles established by Wertheimer (1923) in Research Paper 4.

4) Improving Computational Efficiency - Previous research in map generalization has paid little attention to issues of computational efficiency. As a result, few algorithms for generalization are optimized with respect to efficiency. Due to the large amount of objects that need to be generalized for a typical map sheet, it is desirable to reduce the processing time required for each object. For instance Lecordix *et al.* (2005) give a time of 50 hours for the generalization of just one map sheet in the IGN TOP100 series (without interactive editing). Thus, we are still a long way from achieving real-time generalization. Two approaches are currently being investigated to reduce the processing time. The first approach utilizes machine learning techniques to extract rules that may speed up processing by avoiding unnecessary generalization trials. Work on this subject has been presented by Ruas *et al.* (2006) and Taillandier (2007). The second approach utilizes parallel computing, either on a multi-processor computer or by use of distributed or grid computing. To enable distributed processing on several computers Burghardt *et al.* (2005b) developed a generalization web service framework (see also Neun 2007). Within this thesis we aim to test a third way that uses expert rules, together with information obtained from data enrichment, to control the generalization process more efficiently. Such an enrichment-based approach is possible when using a multi-agent map generalization system that employs a trial and error approach (see Section 2.2.3). Thereby the efficiency of the agent system can be improved if fewer trials are executed to find a good generalization solution. The experiment that should give insight into the question of whether we can improve generalization efficiency based on enriched information and expert rules, is described in Research Paper 3.

We have highlighted four research challenges to be addressed within this thesis and the research papers. More comprehensive lists of research issues for automated map generalization have been compiled by Müller *et al.* (1995b), Weibel and Dutton (1999), and Harrie and Weibel (2007). Specific research issues that have been identified at recent ICA workshops, by representatives of national mapping agencies, can be found in Stoter (2005) and ICA (2004).

4. Summary of Papers

This chapter summarizes the four research papers to provide a basis for subsequent discussion. For every paper we will outline the objectives, methods and results, concluding with the contributions to map generalization research. However, to obtain a comprehensive insight into the methods, problems and achievements, we recommend studying the full papers.

4.1. Research Paper 1: Exploring Object Relations in Maps

Steiniger, S., and R. Weibel (2007): Relations among map objects in cartographic generalization. *Cartography and Geographic Information Science*, Vol. 34, No. 3, pp. 175-197.

4.1.1. Objectives

The first paper responds to the need for an inventory of relations and patterns that appear in maps. Although classifications for relations have been proposed before for GIScience applications, they are insufficient for cartographic purposes, since they focus only on those relations that can be rigorously defined. Maps, however, include relations that are associated to human factors, for instance relations that are associated with visual perception and human cognition. The typology that we propose in Research Paper 1 should include these human components. In developing a typology of relations, we aim to provide a foundation for the analysis and representation of object relations in maps. A thorough analysis and an appropriate representation of relations and patterns, will facilitate the development of contextual generalization operations (i.e. operations that take into account their spatial context) and concurrent treatment of multiple object classes (i.e. operations that consider the relationships between objects of more than one class).

4.1.2. Methods and Results

The typology and its structure have been formulated by studying previous publications on automated map generalization. The overall structure of map object relations that we obtained is shown in Figure 4.1 and consists of three main types:

- *Update Relations* are used for the updating of maps and databases, e.g. when new roads are built and houses are knocked down. They are treated in more detail in Bobzien *et al.* (2006).
- *Vertical Relations* describe relations between objects in maps of different scale, e.g. a soil site in a map of 1:50 000 scale and its corresponding soil aggregate in a map of 1:200 000 scale. These relations are investigated in more detail by Neun and Steiniger (2005).
- *Horizontal Relations* describe the object relations within a single map, e.g. statistical relations for soil classes, or building alignments. Such relations form the focus of Research

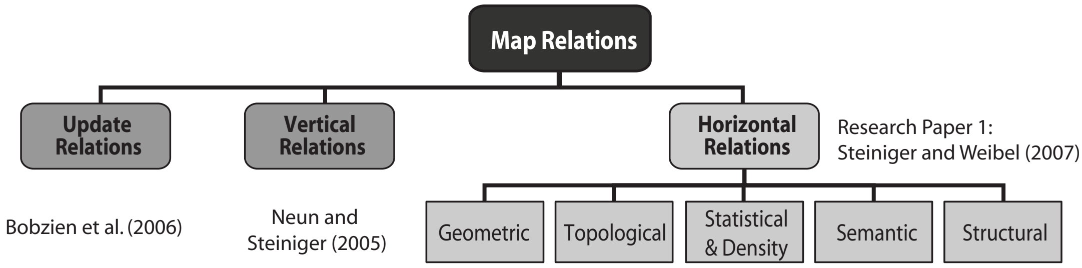


Figure 4.1.: Relations of map objects. Research Paper 1 investigates the branch of horizontal relations that exist in a map.

Paper 1.

To populate the branch of horizontal relations in the typology, we followed two approaches. One the one hand we studied the generalization literature on guidelines for map making, constraints, and measures. On the other hand we visually analyzed a number of topographic and thematic maps. Thereby we tried to evaluate pairs of maps at different scales. The resulting typology of horizontal relations contains 22 types of horizontal relations. Further sub-types are introduced and described in Steiniger and Weibel (2005b). Where possible we also gave references to the literature that employs such relations or proposes methods (i.e. measures) for their quantitative analysis.

4.1.3. Contributions

The proposed typology of horizontal relations enables a structured approach for the characterization of map content. The presentation of an example application for the generalization of islands, emphasizes the utility of the typology (more detail on the islands case study can be found in Research Paper 4). We outline how relations help to characterize a map, how they support the detection of conflicts, and how the relations can inform the selection of appropriate generalization algorithms to solve cartographic conflicts. Finally we present the framework that should enable pattern-aware map generalization (see Figure 1.4), and outline corresponding research needs. One of these needs is a comprehensive set of algorithms for cartographic pattern recognition which can extract the relations of the typology. Research Papers 2 and 4 respond to this need by presenting two approaches for detecting patterns and relations. In this context we identify the evaluation of existing measures and the development of new measures, as major issues to support the analysis of object relations.

4.2. Research Paper 2: Identifying Urban Structures

Steiniger, S., T. Lange, D. Burghardt and R. Weibel (in press): An approach for the classification of urban building structures based on discriminant analysis techniques. *Transactions in GIS*.

4.2.1. Objectives

The second paper presents the first case study on the extraction of a specific geo-spatial pattern. Thereby we aimed at identifying urban building structures that represent distinct semantic concepts for the cartographer as well as for the map user. Having identified the urban structure classes that we wish to extract, we need to formalize the concepts and to develop a recognition approach. Example research questions that emerge from these objectives are: (a) What kinds of urban structures represent useful concepts for map generalization? (b) Which variables and measures can be used to describe the structures? (c) Which classification approach can be applied? and (d) How do the different measures influence the performance of the classification?

4.2.2. Methods and Results

An analysis of maps for different countries (Switzerland, Germany, France and UK) was carried out to identify urban concepts that demand a specific display in maps one the one hand, and are well known to the map reader on the other hand. Five urban concepts (i.e. classes) have been identified: (a) industrial and commercial areas, (b) inner city areas, (c) urban areas, (d) suburban areas and (e) rural areas. The formalization of these five classes is approached by analyzing their visual properties with respect to the building geometries. We found that building size, built-up area density, building shape, and building wall squareness enable a distinction among the classes. We then specified measures that represent these properties and decided to use a supervised[1] classification approach for detecting urban structure classes within a buildings dataset. The results of the supervised classification have been analyzed in terms of classification accuracy. We evaluated the influence of different classification algorithms, the contribution of measures (e.g. to what extent does building wall squareness discriminate inner city buildings from suburban buildings?), and different parameter settings of measures (e.g. the buffer size used for the building density measures). The experiments have been carried out on British and Swiss building datasets. A classification result for the Zurich data is shown in Figure 4.2.

The experimental results revealed that the chosen classification approach is generally successful. We further demonstrated that the accuracy of this urban classification based on building geometries is strongly influenced by the effects of scale (i.e. the corresponding map scale of the building dataset), algorithm parameterization, and regional heterogeneity of the building structures (Swiss vs. English urban areas).

4.2.3. Contributions

The proposed approach for the classification of urban structures realizes the first three stages of a pattern-aware generalization framework. First we identify a useful pattern; then we formalize the pattern based on the geometric relations of Research Paper 1, and finally we develop an approach for the detection of patterns based on the geometric relations. Thus only the two final stages, i.e. the data enrichment and the pattern exploitation, are left for the proof of concept. The exploitation stage will be accomplished in Research Paper 3.

[1] The term 'supervised' indicates that the classification approach requires the user to provide a sample set for every class. This sample set is used to train the classification algorithm (see Duda *et al.* 2000).

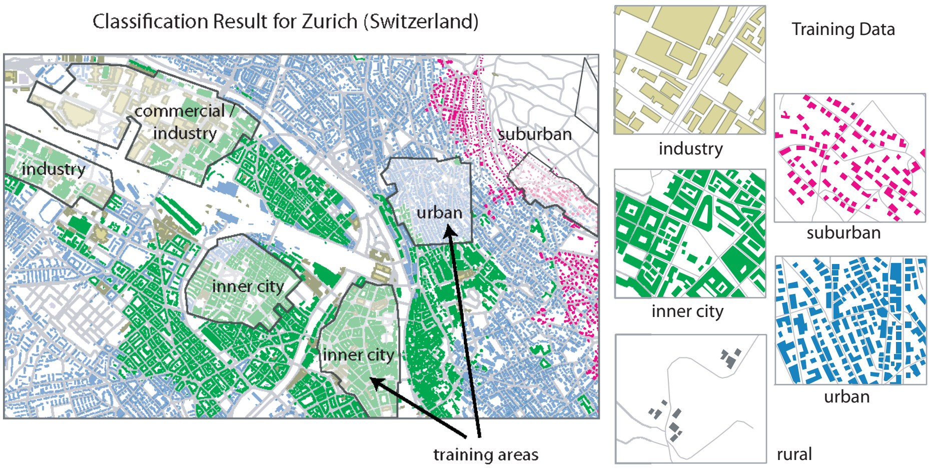


Figure 4.2.: Classifying buildings as being part of inner city area, industrial and commercial area, urban area, suburban area or rural area. (Data courtesy of Swisstopo)

Apart from the contribution of this paper to hypothesis validation, we showed that measures and their parameters should be assessed with regard to their suitability for characterizing a particular pattern. The careful selection and parameterization of measures enables, for instance, the reduction of computational load. We could further show that it is necessary to consider spatial heterogeneity in pattern recognition. For instance the concept of suburban areas can be applied to cities in Switzerland (e.g. Zurich) and Great Britain (e.g. Southampton). However the spatial characteristics of suburban areas, which are reflected in the measure values, can be completely different. As a consequence, we recommend on the one hand to use supervised classification approaches that enable cartographers to define their conception of a particular pattern. On the other hand we recommend an evaluation of spatial pattern recognition approaches in terms of their spatio-cultural application limits.

4.3. Research Paper 3: Use of Detected Urban Structures to Control Map Generalization

Steiniger, S., P. Taillandier and R. Weibel (submitted): Utilising urban context recognition and machine learning to improve the generalisation of buildings.

4.3.1. Objectives

The introduction of automated generalization processes in map production systems requires the processes to be capable of handling large amounts of map data in an acceptable time frame. Furthermore the results should have a cartographic quality similar to traditional manually-created map products. The third paper explores the possibility of improving the efficiency, i.e. the processing speed, and effectiveness, i.e. cartographic quality, of building generalization, by using the information on urban structures extracted using the methods of Research Paper 2. To that end we utilize expert rules for every urban structure class that will control the generalization process for each building. A further aim of the third paper is to test whether improvements in effectiveness can also be achieved by using processing rules obtained from machine learning techniques. Finally, we intended to evaluate the generalization process and the results when expert rules and machine-learned rules are combined to control the generalization.

4.3.2. Methods and Results

To evaluate improvements in generalization efficiency and effectiveness it is necessary to define a reference generalization system. The software that we chose for the testing was the multi agent system *Radius Clarity*$^{\text{TM}}$(see Sub-section 2.2.3). We configured constraints and parameters in the reference system according to recommendations from experts working on the Nouvelle Carte de Base project at IGN France (Lecordix *et al.* 2006). 1:25 000 was chosen to be the target map scale and we restricted the generalization process to individual building generalization. Thus, no contextual algorithms such as typification and displacement were applied. The next step was to automatically generalize a Swiss and a French building dataset with this system. The decisions that were made and the results that were obtained from this initial generalization were logged. From these logged data we used machine learning to determine rules for the process control. Such rules include conditions for the choice of a generalization algorithm, and rules that define when to stop the generalization process for a particular building. At the same time we established expert rules for the urban structure classes from cartographic practice. These rules also define which algorithm should be used next, or which algorithm is preferred over another algorithm. Then we generalized the buildings with the expert rules, with the machine learned rules, and finally with both types of rule together. A sample result processed with and without expert rules is shown in Figure 4.3.

From the results of Figure 4.3 it can be observed that the cartographic quality is increased for the expert rules. In order to evaluate whether the efficiency of computation increases when rules are applied, we created some statistics for the generalization process. The quality of the results was assessed by visual inspection. For the Swiss data we obtained a time reduction for the expert rules by about 15% and for the French dataset a insignificant reduction in processing time (approx. 1%). The application of machine learned rules results in a time reduction of 15% for the Swiss data. Finally the combination of both rule types gained a time reduction of 30% for the French data and 45% for the Swiss data, while the cartographic quality is still better than those of the initial generalization before any rules were applied (denoted as 'normal generalization' in Figure 4.3).

4.3.3. Contributions

The experimental results show that expert rules related to urban building structures enable the quality of generalization results to be improved. Furthermore it has been demonstrated that machine learned rules clearly affect the efficiency of the generalization process in a positive manner. A result that demands further research is the specification of map requirements in terms of constraints. In the experiments we found that the more appealing graphical results are characterized by lower happiness values for buildings, that is, lower satisfaction of generalization constraints (see Figure 4.3). If an inference system is designed to control the map generalization process based on the satisfaction of constraints, then a priority ranking of possible solution approaches (i.e. the application of different generalization algorithms) received from the inference system

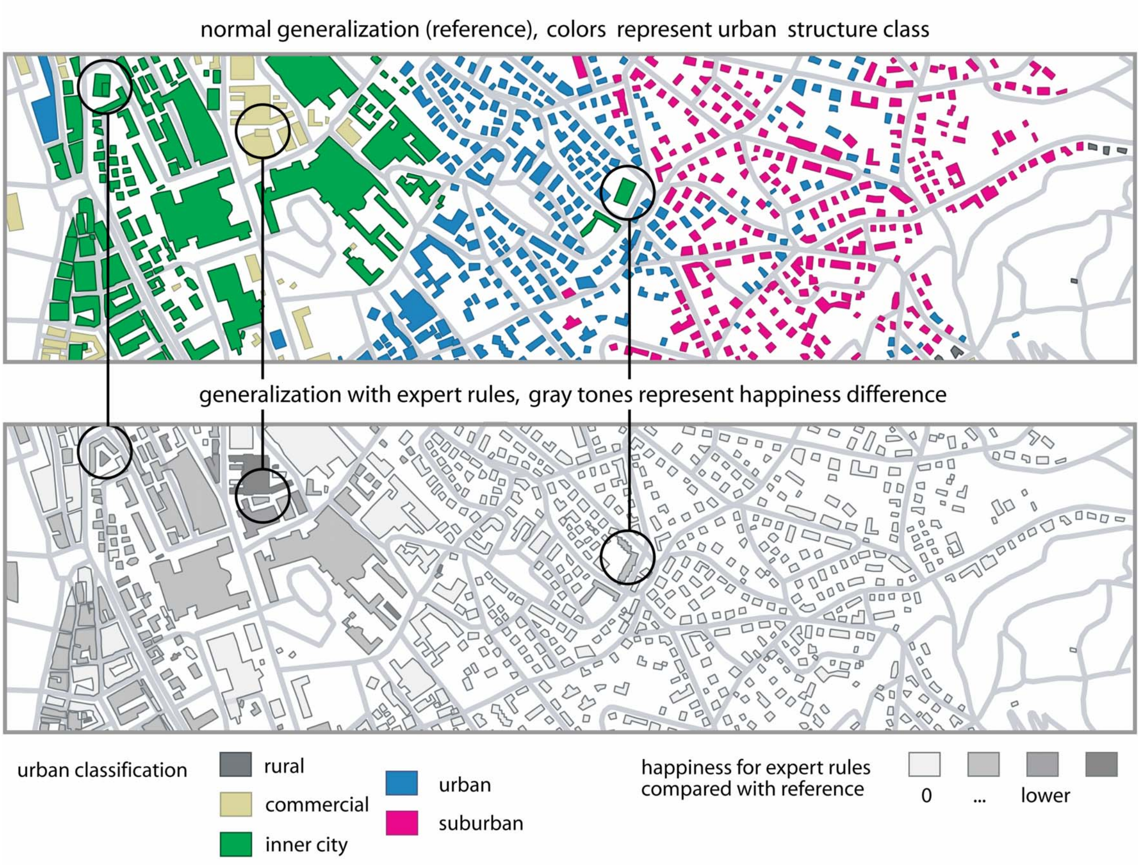


Figure 4.3.: Comparison of automated generalization results without and with expert rules for Swiss data. Note, the happiness value is an aggregated measure for the constraint violations. A high happiness value corresponds to satisfied constraints. (Data courtesy of the City of Zurich, Geomatik + Vermessung, 16.10.2007)

may not match the priority ranking of a cartographer. As a consequence the inference system will favor inappropriate decisions when generalization algorithms are selected.

With respect to the pattern-aware generalization framework, this third paper accomplishes the fifth stage. Stages 1-3 have been realized in Research Paper 2 where the buildings are assigned to urban concepts. Then the data enrichment process is accomplished by storing the assigned urban structure class as an attribute on every building (stage 4). This information is subsequently used by the expert rules to control the building generalization process (stage 5). The experiments show that the urban class-driven generalization control helps to maintain and even improve the quality of the generalization result. Our experiment does not show how the general urban pattern can be preserved, since we investigated only small changes in scale. Such small changes primarily require individual building generalization and rarely result in larger changes of the urban building structure. However, we are confident that the urban structure enrichment can also help to preserve the general urban pattern when medium scale maps of 1:50 000 and 1:100 000 scale are to be derived. Here, large changes in scale have to be accomplished and more a controlled data reduction is necessary, e.g. building elimination.

4.4. Research Paper 4: Detecting Large Island Groups within an Archipelago

Steiniger, S., D. Burghardt and R. Weibel (2006): Recognition of island structures for map generalization. In: *Proceedings of the 14th Annual ACM International Symposium on Advances in Geographic Information Systems*, ACM-GIS'06, Arlington, Virginia, pp. 67-74.

4.4.1. Objectives

A second case study on the detection of specific patterns is presented in Research Paper 4. In contrast to the first case study we did not aim to extract semantic concepts, i.e. a geo-spatial patterns, and instead extracted visual patterns that are induced by human perceptual and cognitive processes. Gestalt theory has extensively dealt with the principles that lead to an organization of perceptual forms (see Wertheimer 1923). We aimed to verify whether these principles hold for objects in maps that are of polygonal shape. If these principles are valid for polygonal objects then they can be used to formalize such perceptual patterns. A formalization will finally enable us to develop algorithms for the recognition of perceptual patterns.

For the validation experiment and the development of algorithms, we decided to use a set of islands as an example. Similar to the first case study on urban patterns we implemented the first three steps of the pattern-aware generalization framework. That is, we identified patterns, i.e. groups of islands, which are considered to be important by the map reader. In the next step we formalized the island groups. Finally in the third step we developed algorithms that identify island groups. The steps of data enrichment and pattern exploitation are not covered by the fourth paper.

4.4.2. Methods and Results

We started our experiment by identifying meaningful groups of islands. To that end we created paper plots representing a set of islands to the south-west of Finland and asked 13 people to mark with a pencil which islands they perceived as groups. We considered island groups to be meaningful if they had been identified by more than one person (Figure 4.4, left). These groups were analyzed visually with respect to the perceptual principles formulated by Wertheimer (1923). We noticed that the people grouped the islands in accordance with Wertheimer's principles. Specifically we recognized six principles that allow a formalization of the groups: (P1) grouping by spatial proximity; (P2) grouping by spatial proximity and by similarity in shape, size and orientation; (P3) grouping by spatial proximity and dominance of a large island; (P4) grouping by proximity and *good continuation*, (P5) grouping by *Prägnanz*, e.g. preference of grouping along horizontal and vertical axes, and (P6) grouping by *past experience*. With respect to these principles we also discovered that the marked groups can be sorted into smaller vs. larger, and elongated vs. compact groups, which enables a further formalization.

Due to the diversity of island groups found we decided to concentrate in the second part of the paper on the detection of only one type of island group. We decided to focus on large island groups that can be described solely by the proximity principle. In order to detect the large island groups we employed a dynamic proximity graph and derived from this graph a minimum spanning tree.

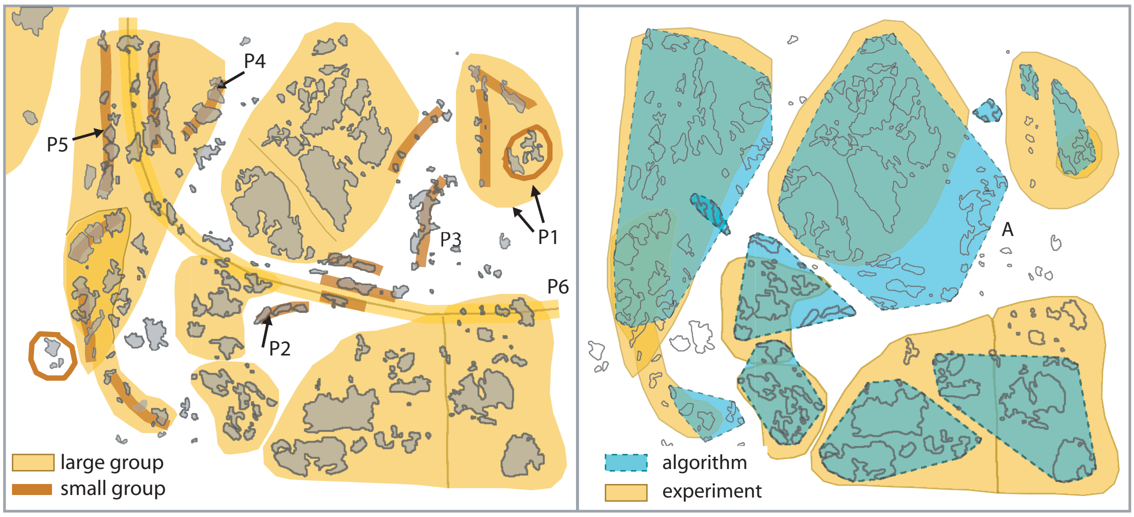


Figure 4.4.: Left: Island groups marked up by the participants of the experiment. Right: Comparison of marked large groups and large groups found by the algorithm. Letter *A* indicates an unnecessary inclusion of a smaller group. (Data taken from Digital Chart of the World)

Splitting this tree at certain positions will yield individual groups of islands. Subsequent merging creates large groups that are comparable to the manually marked groups (Figure 4.4, right). However, the comparison also reveals that the algorithm still has potential for improvements.

4.4.3. Contributions

The results of the human experiment and a comparison with the Gestalt principles indicate that these principles have validity for polygonal map objects, such as islands. In the paper we show further how the principles can be used to formalize perceptual groupings. This enabled us to develop an algorithm that detects large polygon groups formed according to the Gestalt principle of proximity. The formalization of other types of island groups and their detection remains a topic for future research.

With respect to the pattern-aware generalization framework, we could demonstrate that the first three stages of pattern identification, formalization, and extraction can be applied not only to geo-spatial patterns, but also to visual patterns. Although we have not yet shown how the detected groups should be stored for their subsequent exploitation, we have already outlined in Research Paper 1 that island groups deserve a contextual treatment during map generalization. Such contextual treatment will enable the preservation of typical and extraordinary polygonal patterns in maps. Further research should address development of rules for generalization control to allow the maintenance of perceptual (island) patterns.

5. Discussion

In the preceding chapter summarizing the research papers, we presented different approaches and results that should enable a pattern-aware map generalization. In this chapter we will first discuss the outcomes and methods of the publications with respect to the research questions posed in Chapter 1.2. Afterwards we will evaluate the hypothesis against the research results.

5.1. Revisiting the Research Questions

5.1.1. What types of relations exist in maps that can be used to describe patterns?

We addressed this first research question regarding existing relations in Research Paper 1. This paper proposes a typology of horizontal map relations. Five groups of horizontal relations have been identified: geometric relations, topological relations, statistical and density relations, semantic relations, and structural relations. We obtained the typology by analyzing existing maps and the generalization literature. Although we attempted a careful study of maps and the literature, it is possible that further relations may be identified and added to the typology. Research Paper 4 presents a further approach to identify perceptual relations and patterns. Here, we asked people to mark the groups of islands that they perceive. Hence, we used three methods to identify patterns and relations in maps: Firstly, the study of literature on the topic, secondly, the analysis and comparison of maps, and thirdly, interviews of map readers.

A *criticism* that may be made with respect to the established typology of horizontal relations is that we did not clearly discriminate between patterns and relations in accordance with the definitions given in Sub-section 1.1.3. Some of the relations identified, in particular the structural relations, such as *orientation patterns* and *meso structures*, may more readily be denoted as patterns, since they can be seen as composites of other 'atomic' relations. However, drawing the line between relations and patterns is not trivial, since structural relations occur in a variety of forms. Furthermore we believe that some of the structural relations can only be described in parts by 'atomic' relations and not in their entirety. In consequence we decided in Research Paper 1 to focus on an extensive listing that enables a wider awareness of possible relations, rather than presenting a rigorous list that separates between 'atomic' relations and patterns. For a more rigorous typology that accomplishes such a separation it may be necessary to revise the definitions of the used terms 'relation', 'pattern' and 'structure' on the one hand. One the other hand, we need to *formalize* every listed relation, as far as it is possible, to see whether it is an atomic relation or can be composed of others. However, this will be an issue of further research that should be addressed with respect to related disciplines, such as geography, landscape ecology and computer science, since each of those disciplines employ the term 'pattern' as well.

Aside from the terminological issue, the horizontal relations should be classified into generic relations, i.e. relations that are independent from the map theme, and specific relations, i.e. relations that depend on the map theme and map purpose. An example of *generic relations* may be relations and patterns that emerge from human perceptual processes. In combination with assessing the frequency of occurrence of a relation in a map, such a distinction may provide a basis for a priority listing of relations. Such a priority list may guide future research on the formalization of relations, and further define those pattern recognition functionalities which should be part of an automated generalization system.

5.1.2. How can we formalize relations and patterns?

The formalization of relations and patterns has been addressed in Research Paper 2 with respect to urban structures, and in Research Paper 4 regarding island groups. In order to formalize the urban structures we analyzed the geometry of individual buildings in terms of size, shape, and wall squareness, as well as the overall density of the buildings. Thus, we used geometric and density relations to describe the urban structures. Although we focused solely on visual i.e. geometric properties, a description and distinction of urban structures could also be accomplished with additional semantic information. For the formalization of large island groups considered to be meaningful, we again relied only on geometric properties for individual islands (e.g. island size) and on the geometric properties of several islands (e.g. inter-island distance). In this context it has been beneficial to study Gestalt principles of organization. These principles employ geometric object properties and human background knowledge to explain visual groupings of objects. Since our 'pencil and paper' experiment showed that Gestalt principles are applied by humans to organize islands into groups, we can use these principles to formalize the meaningful island groups.

Although we did not experience any *difficulties* in the formalization of large island groups and urban patterns, such difficulties are foreseeable for some of the other relations in the typology. For instance we identified the *generating process* relation that describes whether an object configuration is of a natural or an artificial origin, or whether it is without a distinct structure. Here, every phenomenon (i.e. process) may need its own formalization of the terms 'natural', 'artificial' and 'without structure'.

In Research Paper 1 we introduced a specific relation called *macro-structures*. Such structures are relations that can not be deduced from the map, but are apparent if the map user knows that such structures exist. For example in the experiment on island groups, described in Research Paper 4, none of the participants marked the group denoted by *P6* in Figure 4.4. This island pattern is evident if one studies a larger portion of the archipelago or knows about macro-scale glacial processes that formed the archipelago. If we asked the people during the test whether they could see such pattern, they agreed on its existence. The important point is that on the one hand such patterns are usually known to the cartographer. Consequently this knowledge will influence the map design process, ensuring such macro-scale structures are emphasized. On the other hand the difficulty exists that we cannot formalize such macro-scale patterns with respect to the available data, and that we cannot infer these patterns from the data. This difficulty and the subsequent problems for automated map generalization are probably alluded to by Mackaness (2006) when he cites Minsky (1974) using the words: "*you cannot tell you are on an island by looking at the pebbles on the beach*". Here, the island is a synonym for our macro structure, while the pebbles correspond to the individual polygons. Finally we note that macro structures obtain a special importance for the automated derivation of small scale maps, since larger changes in the map scale can give a new meaning to the sum of things. For instance buildings, parks and roads may be seen as the shaping elements of a town (Chaudhry and Mackaness 2006b).

5.1.3. How can we detect relations and patterns?

In a similar way to the formalization of relations and patterns, we have addressed their detection in Research Papers 2 and 4. Two important factors can be identified that have an *influence* on the successful detection of relations and patterns:

1. The *selection of measures* that are used to quantify an object property. For instance in Research Paper 2 we quantified the building density by means of three buffer measures.
2. The *selection of mapping functions and thresholds* that transform the quantitative measure values into qualitative statements. For instance they are necessary when we wish to distinguish between a natural and an artificial line object.

A careful *selection* of measures is necessary for two reasons: On the one hand the measures should really express what we intend to measure. On the other hand a careful selection can avoid unnecessary computational costs when only few measures are actually required, rather than invoking the entire set of measures. For instance in Research Paper 2 we obtained high correlation for the measures *building area* and *number of building corners* that both quantify the building size. Hence one could discard one of the measures. We also observed that the measures behave differently for British and the Swiss building data and for different parameter settings. Hence, this emphasizes the need to evaluate measures for their explanatory power.

Measures can be applied to every object and every set of objects in the data. The task is then to find a way to *qualify* the *results* of the measure, that is, to determine whether a relation or pattern exists or not, and in addition to qualify the specific type of pattern. Therefore one needs to derive mapping functions and thresholds that allow such a classification. The determination of such functions and thresholds can either be performed by an expert, utilizing supervised learning methods (as in Research Paper 2), or by knowledge acquisition tools, such as *MAACOL* described in Duchêne *et al.* (2005).

Two further issues should be considered when developing and applying computational detection methods. The first issue is that we should not *expect* the computer to detect a pattern that a human cannot discern. For instance in our experiment on urban building classification in Research Paper 2, we observed that our approach has problems in distinguishing industrial and commercial buildings from inner-city buildings. This difficulty has been also noticed by Thomson and Béra (2007), when they asked people to infer visually the function of larger buildings from their depiction in the map. These buildings could occupy functions such as industrial use, educational use, retail, hospital, or office accommodation. Hence, it is not surprising that our classification approach, which utilizes a visual/geometrical description of buildings, has similar limitations to humans when attempting to infer the building function, i.e. urban structure, from form.

Regarding the limitations of detection techniques, we would like to emphasize that the algorithms developed should be assessed in general for their *application limits*. Therefore a first requirement is that relation and pattern detection methods not only provide information on whether a particular relation or type of pattern exists, but they additionally report on the degree of certainty of such a decision. This has been realized, for instance, in Research Paper 2, where the classification algorithm not only delivers the urban structure class but also a certainty value. Although the urban classification algorithm returns a certainty index describing the local accuracy, there is still a need to develop a method which allows the applicability of the classification parameters to be estimated. In Research Paper 2, for instance, we demonstrated that classification parameters deduced from the Swiss building data should not be applied to British building data. Thus, for the example of the urban structure classification we need to identify the spatio-cultural limits for a useful application.

As the concluding remark of this sub-section, we aim to emphasize the importance of *interactivity* with a cartographic or domain expert when relations and patterns need to be detected. Interactivity is necessary for at least three situations: Firstly it is useful to employ supervised pattern recognition approaches where experts can define their concepts. Secondly, experts need to evaluate whether the deduced algorithm parameters are applicable and whether or not detected patterns are meaningful patterns. Thirdly, the experts need to define the relations and structures that cannot be obtained with automated detection methods. All three situations contribute to the realization of the cartographic principle that demands *maps* to be made which are *fit for the purpose*.

5.1.4. How can relations be stored and the data be enriched?

This thesis did not really dwell on this question. The urban structure class obtained for buildings in Research Paper 2 is stored as an *attribute* value attached to every building. In Research Paper 4 the grouping algorithm for the detection of large islands clusters is based on a proximity graph. Therefore every derived group is currently stored as a graph structure that has no connection to the adjacent groups. Storing the groups as a graph can be regarded as storage with a *relation object*. Apart from the possibility of storing relations as attributes and as relation objects, we identified *relation matrices* as a third alternative in Neun and Steiniger (2005). We proposed storage types for the horizontal relations of Research Paper 1 in Steiniger and Weibel (2005b). Two further papers that discuss how the results of data enrichment can be stored and transferred in the context of web generalization services, have been published by Neun *et al.* (2006, accepted).

5.1.5. How can we exploit the enriched data for pattern preservation and process optimization?

The final research question inquires about possible exploitations of the enriched information. The general goal of data enrichment is a characterization of the map data independently from the information needed to run a particular generalization algorithm. Such an algorithm-independent characterization should enable a better preservation of typical configurations (i.e. recurring relations) and unusual configurations (i.e. rare relations), because such characterization allows an improved control of the generalization process. A better informed generalization control encompasses the appropriate selection of generalization algorithms and the choice of the best generalization result from a set of results obtained by applying several algorithms. However, a better characterization may also facilitate the development of new contextual generalization algorithms.

In Research Paper 1 we have conceptually addressed the utilization of relations for the generalization of islands. Thereby we concentrated on how relations can support the evaluation of map constraints and how the detected relations may require new constraints to be introduced. We also mentioned possible applications that support the selection of appropriate algorithms. Later, in Research Paper 3 we presented practical experiments that exploit enriched information, i.e. the urban structure classes, for the generalization of buildings. An improved generalization control has been achieved by introducing expert rules that propose suitable generalization algorithms according to the classification of a building. For instance we enforced the elimination of small buildings in dense *inner city* areas to retain space, while we prohibited elimination in *rural* areas, where even small houses can be important landmarks. During the experiment which focused on deriving rules with machine learning techniques, we recognized that some of the obtained rules used the urban classification in the conditional part of the rule. Hence, the characterization of buildings with their urban structure class provided some additional information that was useful for optimizing the control of the generalization process.

Apart from the exploitation of enriched information for the process control, we also imagine that the urban structure classification could be used to create thematic maps. For instance the five urban structure classes were defined by analyzing existing maps, including a regional topographic map and a school map (see Research Paper 2). Accordingly, the classification can also be utilized for generating such maps.

5.2. Evaluating the Hypothesis

In Section 1.2 we established the following hypothesis:

> "Data Enrichment enables pattern-aware map generalization that results in an improvement of the quality of the generalization results and in an improvement of the efficiency of the generalization process".

This hypothesis and the research objectives have led to the introduction of a conceptual data enrichment framework that enables the preservation of patterns during map generalization. With the proposed framework we aim to contribute to an improvement of quality by outlining the steps necessary for the maintenance of patterns during map generalization. In order for automated generalization techniques to be introduced in map production, there must be an improvement in the efficiency of the generalization process, i.e. a reduction in the time needed to generalize a map. We outlined in Section 3.3 that current generalization systems are not able to generalize a map sheet in real-time and that the development of methods for the reduction of processing time is one objective of current research at national mapping agencies.

The *evaluation* of the hypothesis is accomplished in Research Paper 3, where we introduce expert rules to improve the quality and the efficiency of building generalization for a scale change from 1:10 000 to 1:25 000. It has been noted that such a small change of scale requires only individual building generalization in the majority of cases. Thus, generalization of individual buildings will rarely result in changes in the urban structure and therefore the general urban pattern will be maintained. However, the results show that an *improvement of quality* is possible, although we only applied rules for the generalization of individual buildings (see Figure 4.3). In more detail we could use expert rules to prevent excessive changes of the shape of buildings. If the rules are not applied, then the generalization results for some of the buildings are visually not satisfying. Furthermore overlap conflicts between buildings may occur in inner city and urban areas due to significant changes in the building shapes. Such overlaps necessitate excessive building displacement, which may eventually result in distortions of urban building blocks. With respect to the second aim that focuses on an *improvement in efficiency*, we did not obtain clear results. While we could notice a time reduction of 15% for the Swiss building dataset, we achieved no significant time reduction for the French dataset. In addition to this result we have to note that the data enrichment itself is also a time consuming process. For instance the calculation of the geometric indices and the subsequent urban building classification took more than one hour for approximately 24,500 buildings in the Zurich dataset. However, data enrichment is a one-off cost strategy. This is superior to those contextual generalization algorithms that employ implicit knowledge, requiring repeated computation of the same contextual analysis.

Based on the current experimental results we *conclude* that the first part of the hypothesis was verified, which promises an improvement in generalization quality. For the second part of the hypothesis, which predicts an improvement in efficiency, we can neither verify nor reject it. An exhaustive evaluation that shows whether a reduction in processing time is possible remains the objective of further experiments. We recommend that such experiments focus on larger scale changes, e.g. from 1:10 000 scale to 1:50 000 scale, since more topographic detail needs to be reduced, and additionally contextual operations, such as aggregation and typification, must be applied (Müller 1990). Thus, there is more potential for influencing the control and selection of generalization algorithms.

6. Conclusions and Perspectives

In this chapter we present the main contributions of the thesis to map generalization research. We will subsequently outline the possibilities for applying the developed methods and results to other fields. Finally we summarize the research needs identified during the work on this thesis.

6.1. Main Contributions

The *objective* of this thesis has been to develop an approach that enables pattern-aware map generalization. Thereby we strove to account for three requirements: Firstly, we aimed to separate the types of knowledge identified by Armstrong (1991), i.e. structural, geometrical and procedural knowledge. Secondly, structural knowledge should be explicitly modeled and not be hidden in the algorithms. Thirdly, the approach should be able to link geometrical and structural knowledge on the one hand and both types of knowledge to procedural knowledge on the other hand, to enable an informed control of map generalization. In consequence a conceptual framework that realizes a data enrichment strategy has been developed. The framework is composed of five components: 1) pattern and relation identification, 2) formalization of patterns with relations, 3) extraction of relations, 4) storage of relations, and 5) utilization of relations (see Figure 1.4).

To show the applicability of the framework we analyzed and specified the five components with respect to *two case studies*. In the first case study we aimed to identify and extract urban structure classes. Such urban structures present a higher order semantic concept that is also applied by cartographers to map generalization. For instance, inner city areas are differently treated than suburban or rural areas (SSC 2005). In the second case study we considered groups of islands. Here, we focused on island groups that evolve from human perceptual and cognitive processes. The preservation of such perceptual patterns is one of the main interests in map generalization.

From our work on these two case studies we now identify the following points as *our major contributions* to map generalization research:

- We established a comprehensive *typology of horizontal relations* (and patterns) that we derived from an analysis of topographic maps, thematic maps and the cartographic literature (see Research Paper 1). Thereby we consider it to be an important point that the typology also encompasses relations that appear in thematic maps and not just the relations of topographic maps. To the author's knowledge such an inventory has not been established before.
- We showed for both case studies how *identification* and *formalization* of patterns by use of the relations can be accomplished (Research Papers 2 and 4). For the identification we used different knowledge acquisition methods that have been proposed by Weibel *et al.* (1995), such as user observations, questionnaires, and literature on the subject. For the formalization of the island groups, identified in a 'pencil and paper' experiment, we could

utilize the *Gestalt principles* established by Wertheimer (1923).

- We developed a supervised classification approach to *detect* five different types of *urban structure* (Research Paper 2). In a number of experiments we demonstrated the influence of the chosen discriminant analysis algorithms, as well as the contribution of different geometric and structural measures to the classification results.
- Influenced by the study of Regnauld (2001) that utilizes a minimum spanning tree (MST) technique to detect building groups, we developed an MST based approach to *detect large island groups* (Research Paper 4). Subsequently we proposed a utilization of Principal Component Analysis to *describe the groups* in terms of their shape (i.e. clustered vs. elongated) and orientation.
- Finally we *exploit the horizontal relations* to better control the map generalization process (Research Paper 3). Thereby we discussed the applications theoretically for islands, and conducted practical experiments to exploit the urban structure classification of buildings. The introduction of expert rules for the selection of generalization algorithms demonstrated an improvement in the quality of the generalization result.

Apart from these methodical and practical contributions we *identified* two *issues* that should be considered in future map generalization research:

- We highlighted in the Discussion (Sub-section 5.1.3) the importance of *interactive components* in a generalization system. Interactivity is necessary because an expert should decide if a detected pattern is meaningful for the map purpose (see also Fuchs 2002). Furthermore the expert must be able to specify patterns that we are not able to detect using automated approaches, for instance the macro-structures discussed in Sub-section 5.1.2. Such a necessity of interaction has also recently been pointed out by Mackaness (2006).
- We discussed how important it is to *evaluate pattern detection algorithms* and hence existing contextual generalization algorithms for their applicability and (spatial) limits. This requirement is a consequence of results obtained from the urban structure classification experiment on two building datasets from different countries (see Research Paper 2).

We hope that these results and statements facilitate further research on the characterization of maps to improve generalization process control. Improvements in characterization and process control should result in an increased quality of generalization results, in terms of pattern preservation, and also enable an improvement in efficiency. We believe that the typology of horizontal relations is an important contribution which advances generalization research on thematic maps. Due to its modular structure we also believe that the data enrichment framework itself can act as a guideline for the development of new contextual generalization algorithms.

Apart from the contributions to map generalization we see the possibility that the data enrichment framework and the results that we presented may be useful *beyond map generalization*. A first application domain that we could identify is the field of *spatial cognition and wayfinding*. Here, our developed data enrichment framework and the typology of horizontal relations can support the formalization and extraction of geometric and spatio-structural components of salience to detect landmarks. This is exemplified by Sester and Elias (2007) who emphasize and show the relevance of cartometric analysis methods for the extraction of landmarks. Furthermore they discuss the generalization operations that are relevant for the display of generated wayfinding routes.

Two further domains to which we think our work can make a contribution are *urban modeling* and *environmental modeling*. For instance, Herold *et al.* (2003, 2005) conduct a spatio-temporal analysis of urban growth, using a set of spatial metrics that implement the structural and statistical relations of our typology of horizontal relations. In environmental modeling we regard pattern-preserving data generalization as an essential component to provide consistent input data for models that focus on different spatial scales. For example Canada's National Forest Carbon Accounting Framework focuses on a modeling and reporting strategy at four different scales: 1) national scale, 2) regional and provincial scale, 3) operational management units, and 4) stand level (Wulder *et al.* 2004, Kurz and Apps 2006). Input data for the carbon modeling, that are consistent among the four scales with respect to the information relevant to the modeling, are required for the evaluation and comparison of the modeling results.

Finally a possible fourth application field for our developed methods is *geographic information retrieval*. The request of web searches that include spatial components[1] with internet search portals, such as Google™or Yahoo™, requires the data enrichment of geographic databases, to allow an interpretation of spatial terms, and the annotation of web pages with spatial information (Egenhofer 2002, Purves and Jones 2006). Transforming qualitative geographic terms such as 'near' Zurich and 'in' Zurich into a quantitative description can, for instance, be accomplished using the urban classification approach presented in Research Paper 2. To define the relation "*in* Zurich" one would probably exploit the distinction between rural and non-rural areas in order to extract the 'footprint' of the city of Zurich. We also believe that the typology of horizontal relations may help to formalize spatial terms that describe relations between specific objects (e.g. Lake Zurich and Zurich) and object classes (e.g. Lakes and Cities) to later use such formalization for spatial analysis and data enrichment.

For the four fields presented above, we see benefits when a spatial analysis is performed that seeks to uncover the spatial relations in the data, and when the results obtained from the analysis are used to enrich the original data. The developed data enrichment framework with its five steps may probably remain the same for all fields. Only the step that covers the exploitation of the detected patterns and relations will be different for every application.

6.2. Summarized Research Needs and Outlook

Several issues for further research emerge from the work presented in the four research papers. We identify three main topics, where each topic entails different research issues.

1. Formalization and Detection of Patterns and Relations - In Research Paper 1 we proposed a basic set of horizontal relations that can occur in maps. What we have not completed yet is the development of a full set of measures to detect them. Since a certain number of relations are theme-dependent and others occur very rarely, it is useful to identify a set of generic and important relations that should be addressed in the first instance. Thereby the term 'important relation' needs to be defined first, for example with respect to the frequency of occurrence. A similar situation occurs for patterns. We presented only two case studies that describe a semantic (i.e. geo-spatial) pattern and a visual pattern with those relations. Here the need also exists for identifying those patterns that are particular meaningful for automated map generalization, and to formalize them with the relations of the typology. The development of methods for the detection of 'important'

[1] Queries such as "hotels in the city of Zurich" or "all lakes near Zurich".

relations and patterns should address the four following challenges:

- Identification and development of measures that can be used to describe a horizontal relation.
- Evaluation of measures, i.e. whether they really describe what we aim to describe.
- Identification of application limits for measures and pattern detection algorithms with respect to the geographic context and data resolution.
- The development of pattern recognition algorithms that do not only identify a particular pattern or classify a situation but also provide a (certainty) index that describes how well detected pattern and pattern prototype match with each other.

These four points present general challenges for the development of spatial pattern detection methods. A rather specific challenge with reference to the continuation of the presented work is the formalization and development of pattern recognition methods for small island groups. These groups are not only formed by the principle of spatial proximity but also by other perceptual principles (e.g. *Good Gestalt* principle and *Prägnanz* principle). We consider it to be an interesting task to develop algorithms that realize these other perceptual principles. Interest in the development of such algorithms exists probably not only in cartography, but also in the fields of computer vision and artificial intelligence.

2. Constraints for Map Generalization Control and Evaluation - One of the results of Research Paper 3 was that visually observed map quality was not appropriately represented by the constraint satisfaction values. We observed that the summarized satisfaction for several commercial and inner city buildings was actually lower for visually more appealing results, than for the results which failed to conform to some of the cartographic requirements. Since the constraint satisfaction influences which generalization algorithm will be applied next, wrong decisions regarding which algorithms to apply will made in the case of inappropriate constraint definitions, and visually more appealing generalization results might be discarded. We suggest three approaches to tackle this problem:

- Evaluation of measures for their applicability to formalize a certain constraint. This includes a further evaluation of the mapping from quantitative measure values to qualitative satisfaction values.
- The development of new constraints that account for a specific context (e.g. rural or inner city buildings) and not for a complete class of objects (e.g. all buildings or roads). Such constraints may emerge from the analysis of horizontal relations in the typology.
- The development of adaptive constraint weighting and aggregation schemes that enable a context dependent objective function to be established. Research on this subject is currently being carried out at the COGIT lab at IGN France.

The second of the above approaches, which suggests the development of contextual constraints, facilitates the treatment of two types of map situations. On the one hand we can better describe requirements for the generalization of objects groups. For instance when generalizing alignments of islands, it would be useful to introduce constraints that describe the maximum allowable distortions of position and size relations between individual islands in an alignment, but also to introduce constraints that preserve the overall group properties (e.g. shape, orientation). A first attempt at listing constraints for polygon generalization, which also includes contextual constraints, was proposed by Galanda (2003a). However we think that some of the constraints need to be revised with respect to the typology developed here and the case study carried out on island generalization. On the other hand we need to consider the relations and conditions between different themes in more detail. For instance it is necessary to propagate displacement of rivers to the surrounding contour lines, to prevent the generalized rivers being represented as flowing up-hill in certain places. Such inter-theme effects have been shown for instance by Gaffuri (2005), who also presents a first solution approach to the problem in Gaffuri (2006).

3. Advanced Generalization Control - We have emphasized previously that an interactivity component in the process modeling is a requirement for pattern-aware generalization. Such a component is required to allow the expert to decide whether detected relations and patterns are meaningful for the purpose of the map. Apart from the possibility of confirming patterns, the domain expert and the cartographer may also be allowed to define their own patterns. The introduction of an interactive modeling component raises at least three questions:

- How can we display the detected relations and patterns? This question needs to consider the different types of relations, i.e. vertical, horizontal and update relations, but also the levels that are addressed by the relations, i.e. single object, group, or class.
- What tools are needed to define relations and patterns and to confirm detected patterns?
- How can interactive components be integrated into automated map generalization frameworks?

A possible approach that integrates interactive and automated components has been proposed by us in Steiniger and Weibel (2005a). There we suggest a conceptual framework for thematic map generalization that builds on a fusion of workflow systems and the multi-agent approach. A first attempt to integrate an agent-like model with a workflow model has been reported by Monnot *et al.* (2006). Also Petzold *et al.* (2006) focus on constraint-based map object generalization that can be controlled interactively with a workflow system.

Apart from the introduction of interactive modeling components, it is necessary to develop new or modify existing contextual generalization *algorithms*. Most of the current algorithms, for instance algorithms for building typification, use *implicit* knowledge to solve complex cartographic conflict situations. The new or modified algorithms should allow either a flexible control by parameters, which are chosen according to the enriched information, or should allow the provision of *explicit* knowledge. The obtained flexibility in algorithm control should enable us to adapt the generalization algorithms better to specific situations (e.g. a different parameterization for building typification in inner city and suburban areas) and will hopefully result in more appropriate solutions. However, along with this enhanced flexibility comes an additional duty to evaluate and document working application cases and the application limits of the algorithms. Otherwise the user will be condemned to perform time-consuming trial-and-error experiments for determining appropriate parameter settings.

The most prominent issues include: 1.) the formalization and detection of a key set of relations of the typology, 2.) the specification of contextual and group-related constraints, 3.) the development of interactive pattern definition and confirmation tools, and 4.) the design of flexible and controllable generalization algorithms. Once these issues have been solved, we can tackle practical solutions to problems such as the island generalization example, discussed only theoretically in Research Paper 1. Another 'simple' example of polygon generalization would be to realize the lake region generalization example presented by Bertin (1983). Both examples are simple in the sense that one needs only to consider one thematic layer (islands or lakes), the patterns are basically visual patterns, and one needs only to account for polygons, i.e. one geometry type. However both examples may provide useful initial insights, before more complex scenarios are tackled such as the generalization of geological maps.

Geological maps can contain several geological themes but also display topographic information. This requires maintenance of the consistency between the different information layers during the generalization process. Furthermore we can deduce from the examples presented, along with the typology of horizontal relations, that geological maps must contain a larger set of relations compared to the island example, including visual as well as semantically meaningful patterns. Subsequently new tools for pattern detection, visualization and confirmation, as well as an enhanced set of constraints and generalization algorithms must be developed to enable a pattern-aware generalization of such complex thematic maps. We believe that previous research on automated topographic map generalization (see Mackaness *et al.* 2007), on polygon generalization algorithms (see Jones *et al.* 1995, Bader and Weibel 1997, Galanda and Weibel 2003), and on constraints for polygon generalization (Galanda 2003a) provide a good foundation tackling these issues in future research. We also believe that this thesis has made useful contributions to establishing an automated thematic map generalization system, by providing a typology of horizontal relations in maps, a pattern-aware map generalization framework, and two cases studies that focused on the extraction of visually and semantically meaningful patterns in maps.

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Zhang, Q. (2004b), Road network generalization based on connection analysis. In: *Developments in Spatial Data Handling*, P.F. Fisher (ed.) (Berlin: Springer Verlag), pp. 343–353.

A. Curriculum Vitae

STEFAN STEINIGER

born on 16th of November, 1976, in Magdeburg, Germany
citizenship: German

EDUCATION

1993–1996	Abitur (A-Level), Technisches Gymnasium Chemnitz, Chemnitz, Saxony (extended secondary school) majors: civil engineering and mathematics
1997-2003	Studies of Geodesy and Cartography at the Technische Universität Dresden. Specialization: geodata processing and global geodynamics (i.e. planetary gedoesy).
1999	Undergraduate diploma (Vordiplom) in Cartography, Technische Universität Dresden
1999	Undergraduate diploma (Vordiplom) in Geodesy, Technische Universität Dresden
Mai 2003	Diploma Thesis (MSc.) in Geodesy at Technische Universität Dresden entitled: "Vergleichende Untersuchungen zur Linienglättung mit Snakes und Wavelets." (Comparative Tests on Cartographic Line Smoothing Using Wavelets and Active Splines.) advised by Prof. Dr. Siegfried Meier.
2004-2007	Ph.D. student in Geography at University of Zürich.
2007	Ph.D. thesis in Geography, entitled: "Enabling Pattern-Aware Automated Map Generalization" advised by Prof. Dr. Robert Weibel and Dr. Dirk Burghardt.
since 2004	Research assistant on the Swiss NSF founded project DEGEN within the Geographic Information Systems Group, University of Zurich.

Zurich, 31st of Mai 2007

B. Publications

List of own publications and unpublished works until June 2007 sorted by year.

Year 2004

Steiniger, S. and S. Meier (2004): Snakes: a technique for line smoothing and displacement in map generalisation. *7th ICA Workshop on Generalisation and Multiple Representation*, Leicester, GB. http://ica.ign.fr/ (accessed on 01 June 2007).

Year 2005

Burghardt, D., and **S. Steiniger** (2005): Usage of principal component analysis in the process of automated generalisation. In: *Proceedings of the XXII Int. Cartographic Conference*, La Coruña, Spain, (CD-ROM).

Meier, S. and **S. Steiniger** (2005): Linienglättung mit Snakes als Filteroperation. *Photogrammetrie, Fernerkundung und Geoinformation* (PFG) 8(4): 311- 320.

Neun, M., and **S. Steiniger** (2005): Modelling cartographic relations for categorical maps. In: *Proceedings of the XXII Int. Cartographic Conference*, La Coruña, Spain, (CD-ROM).

Steiniger, S., and R. Weibel (2005a): Relations and structures in categorial maps. *8th ICA Workshop on Generalisation and Multiple Representation*, La Coruña, Spain, http://ica.ign.fr (accessed on 01 June 2007).

Steiniger, S., and R. Weibel (2005b): A conceptual framework for automated generalization and its application to geologic and soil maps. In: *Proceedings of the XXII Int. Cartographic Conference*, La Coruña, Spain, (CD-ROM).

Year 2006

Steiniger, S. (2006): Classifying urban structures for mapping purposes using discriminant analysis. In: G. Pristnall and P. Aplin (eds): *Proceedings of GIS Research UK (GISRUK 2006)*, Nottingham, UK, pp 107-111. [extended abstract]

Steiniger, S., D. Burghardt and R. Weibel (2006): Recognition of island structures for map generalization. In: *GIS '06: Proceedings of the 14th Annual ACM International Symposium on Advances in Geographic Information Systems*, Arlington, VA, pp. 67-74.

Steiniger, S., M. Neun and A. Edwardes (2006): *Lecture Notes: Foundations of Location Based Services.* Department of Geography, University of Zurich.

Steiniger, S., R. Weibel and D. Burghardt (2006): Recognition of large island structures for map generalization. In: M. Raubal, H. J. Miller, A. U. Frank and M. Goodchild (eds): Geographic Information Science. 4th Int. Conf., GIScience 2006, Münster, *IfGIprints* 28, pp. 351-354. [extended abstract + poster]

Year 2007 **Steiniger, S.**, and P. Taillandier (2007): Improving map generalisation of buildings by introduction of urban context rules. In: *Proceedings of GeoComputation 2007*, Maynooth, Ireland. [extended abstract]

Steiniger, S., and R. Weibel (2007): Relations among map objects in cartographic generalization. *Cartography and Geographic Information Science* 34(3): 175-197.

Forthcoming **Steiniger, S.**, T. Lange, D. Burghardt and R. Weibel (in press): An approach for the classification of urban building structures based on discriminant analysis techniques. *Transactions in GIS*.

Steiniger, S., P. Taillandier and R. Weibel (submitted): Utilising urban context recognition and machine learning to improve the generalisation of buildings.

Part II.

Research Papers

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Relations among Map Objects in Cartographic Generalization[1]

Stefan Steiniger and Robert Weibel

ABSTRACT: Adequate representation of cartographic expert knowledge is essential if maps are to be created in an automated way. Part of this expert knowledge is made up by the structural knowledge embedded in the relations that exist among the objects depicted on a map, as these define the structures and patterns of the corresponding real-world objects that should be maintained and emphasized in the cartographic generalization process. With this article we aim to provide a foundation for the analysis and representation of such relations among objects in thematic and topographic maps, which we term horizontal relations. We start off by defining the terminology underlying map object relations and by discussing how these relations interact with map constraints and cartometric measures. We then present a typology of horizontal relations that may be found in a map with respect to map generalization. The typology is the result of a study of thematic and topographic maps, as well as an analysis of the literature on the use of map object relations. Five different types of horizontal relations are identified: geometric, topological, semantic, statistical and structural. Some of these can be based on standard operations available in commercial GIS or mapping systems, while others are less easily accessible. To demonstrate the use of our typology and show how complex horizontal relations can be formalized, we present an application of the typology to the grouping and generalization of islands. Subsequently we discuss the various steps involved in the usage of horizontal relations in map generalization, as well as their associated roles.

KEYWORDS: map generalization, map object relations, horizontal relations, structure recognition, data enrichment, cartometrics

Introduction

In the last decade, research in automated map generalization reached a point where automated methods were continuously introduced into map production lines. Reports on the successful and ongoing integration of automated map generalization procedures have been published, among others, for the production of topographic maps at IGN France (Lecordix et al., 2005) and the Ordnance Survey of Great Britain (Revell et al., 2006). Most of the automated procedures used in operational production lines, however, are limited to rather isolated operations or applied independently to individual map objects (e.g. shape simplification) or to objects of a single object class (e.g. typification of buildings). While it is possible to achieve considerable productivity gains with such generalization operators (Lecordix et al., 2005), it is also clear that further progress can only be made if research will deliver solid solutions for *contextual* generalization operators (i.e. operators taking into account their spatial context), as well as for the *concurrent* treatment of multiple object classes (i.e. operators considering the mutual relationships among objects of more than one class). While the development of contextual operators for individual object classes is clearly on the way (e.g., Ware and Jones, 1998; Bader et al., 2005), the development of methods that can deal with multiple object classes is still in its infancy. One of the rare examples is Gaffuri (2006), who reports on a first attempt to treat simultaneously different object classes. We argue that an agreement about the kinds of spatial and semantic relations that exist among objects in a map, as well as methods to formalize, detect, and represent such relations, will be essential prerequisites to the progress of research in this area.

A simple example of four lakes, shown in Figure 1, should help to illustrate the necessity of representing the structural knowledge embedded in contextual, inter-object relations. A well legible map should meet

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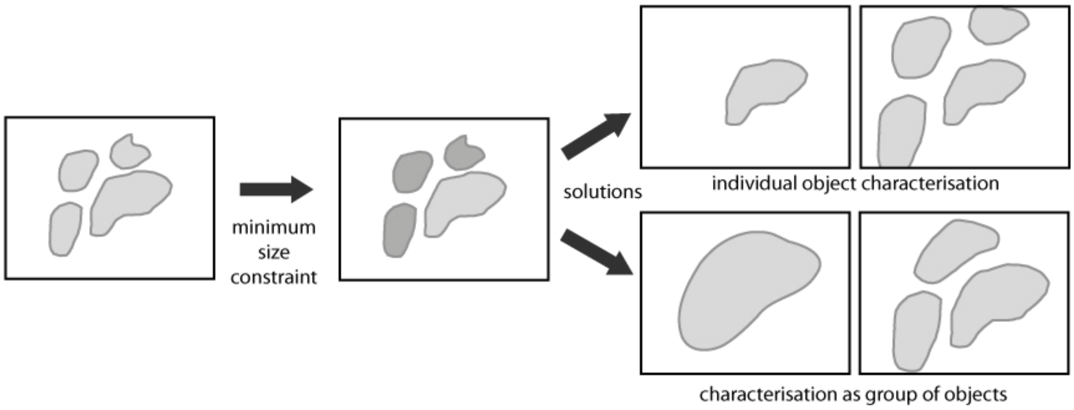

Figure 1. Different generalization solutions if contextual relations are ignored (top-right) and observed (lower-right).

several visual requirements, including that map objects should have a minimum size to be unambiguously perceived by the map reader. In our example, we assume that three of the lakes would not meet this constraint for a particular target scale. Now, we have to decide how the problem can be solved. On the top right of Figure 1, two simple solutions are shown that ignore the contextual situation, either deleting the three small lakes or enlarging them individually until they have reached the minimum size, respectively. These solutions both meet the basic perceptual requirement (minimum size), but do not necessarily represent a good cartographic solution from a structural point of view. A more adequate solution should also maintain the typical structures or patterns that extend across map features and thus emphasize the specificities of the map. Such a solution can only be obtained by considering inter-object relations. Both solutions shown in the lower-right corner of Figure 1 better preserve the typical properties of the spatial arrangement, as well as the size and shape relations, among the objects involved.

In this article, we propose a typology of relations among map objects aimed to act as a foundation for future research on developing new methods for contextual generalization involving objects from multiple object classes. The typology should offer a basic set of elements to represent the structural knowledge necessary to characterize the relation types occurring in both topographic and thematic maps, and inform the selection and parameterization of contextual generalization operators.

The idea outlined above, to characterize a map with relations and to store the characterization results to support subsequent decision processes, has also been pursued by several other authors. In the map generalization community the idea is generally known today as 'data enrichment' (Ruas and Plazanet 1996, Neun et al. 2004) and the sub-process of context analysis is known as 'structure recognition' (Brassel and Weibel 1988) or 'structure analysis' (Steiniger and Weibel 2005a). Even though data enrichment and associated processes have been around for a while, to our knowledge no author has yet attempted to establish an inventory of possible map object relations. Until today, the discussion of (spatial) context relations in map generalization has either remained on the general level (Mustière and Moulin 2002) or focused on the analysis of rather specific scenarios. Examples of the latter include the detection of groups of buildings and the modeling of relations among roads and buildings (Boffet 2001, Regnauld 2001, Duchêne 2004).

The remainder of the paper is organized as follows. The second section introduces the necessary definitions as a foundation of the subsequent sections. The third, central section introduces the proposed typology of horizontal relations. It starts off with a short review of existing, related typologies in order to derive the structure of the proposed typology. Following that, the set of relations is presented, and existing work is discussed. In order to demonstrate the utility of our typology and show how complex relations can be formalized, the fourth section then offers an example on the grouping and generalization of islands. This is followed by a section discussing the various steps of the utilization of map object relations, including directions for future research. Finally we summarize the main insights of the paper. Note also that an extended version of the proposed typology has been presented in Steiniger and Weibel (2005b).

Defining Object Relations in Maps

Before we present our typology, it is necessary to define the underlying terminology. We start with definitions of the different types of relations that are particularly relevant in the context of map generalization and multiple representations. Then, we discuss the interactions between relations, constraints, and measures.

Horizontal, Vertical and Update Relations

In mathematics, "relations" denote arbitrary associations of elements of one set with elements of other sets. Depending on the number of sets that are involved, the relations are termed unary (involving only elements of one set), binary (involving associations of elements of two sets) or *n*-ary (involving elements of multiple sets). While we embrace the mathematical notion of the term "relation", we are only interested in those relations that are relevant for map generalization. In map generalization, the notion of scale, resolution or level of detail (LOD) plays a crucial role, leading to the definition of the first two classes of relations, termed *horizontal relations* and *vertical relations*, respectively. Since map generalization is a process leading to modifications of the content of a map or map database, we further define *update relations* as a third relation class.

Horizontal relations: These relations of map objects exist within a single scale, resolution or level of detail (LOD) and represent common structural properties – e.g. neighborhood relations and spatial patterns (Neun et al. 2004). For instance, in a geological map polygons of a particular rock type that are close to each other form a group, while polygons of another rock type that are also close to each other can be seen to form another group (see Figure 2). The rock polygons now have a relation to the group, being part of it or not, and the two groups of rocks have a relation to each other as well (e.g., an exclusion relation, and a distance relation).

Vertical relations: This class of relations links objects and groups among different map scales, resolutions or levels of details (LODs). For instance, polygons of a particular soil type in the geo-database of scale 1:25,000 are linked to the generalized soil polygons in a database of scale 1:500,000 (see Figure 2, right). Note that the cardinality of such relations may vary between nullary, unary, and *n*-ary. Thus, a soil polygon at 1:25,000 may not have a homologous object at 1.500,000; it may have exactly one correspondent; or several polygons at 1:25,000 may be aggregated to one polygon at 1:500,000.

Update relations: This relation class is used to describe changes of map objects over time. According to Bobzien et al. (2006), this relation has three states: insert, remove, and change. As an example for the application of update relations one might think of a building that has been newly constructed (action: insert), extended (action: change), or knocked down (action: remove) since the last revision of the corresponding map or spatial database has been published.

The concepts of horizontal, vertical, and update relations are not new. For instance, horizontal relations –

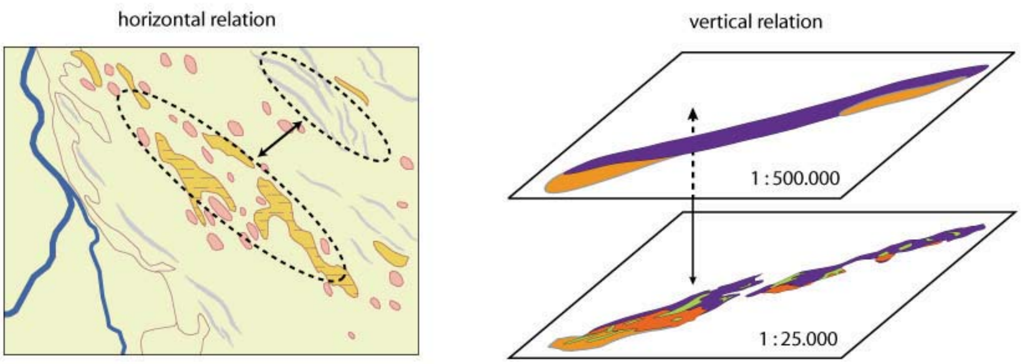

Figure 2. Horizontal relations (left) and vertical relations (right) in categorical maps. Data: © FOWG (for an explanation of acronyms see Acknowledgments).

though not termed that way – have been extracted and utilized for the generalization of buildings and settlements in the form of towns, districts, urban blocks, building groups and building alignments by Gaffuri and Trévisan (2004). Vertical and update relations are a well known concept used in Multiple Representation Databases (MRDBs). The use of vertical relations (commonly termed 'links' in the MRDB literature) has been demonstrated, for instance, by Hampe and Sester (2004) for the display of topographic data on mobile devices. Update relations that describe propagated updates of data within a MRDB were initially described by Kilpeläinen and Sarjakoski (1995).

A note should be made here on the naming of the relation classes: We use the terms horizontal relations and vertical relations as we believe that on the one hand they are intuitive to understand and on the other hand these linguistically similar terms indicate that they form a pair, yet are different. Obviously, these terms should not be understood in the geometrical sense. Rather, they make use of the picture of a stack of data layers (or maps) of different scales, where horizontal relations only affect a single layer (or resolution), while vertical relations extend across the entire stack of (resolution) layers. Other, equivalent terms have also been used, such as 'intra-scale' and 'intra-resolution' for 'horizontal' as well as 'inter-scale' and 'inter-resolution' for 'vertical' (Bobzien et al., 2006).

This paper intends to offer a more comprehensive and systematic discussion of horizontal relations in map generalization than has been available from previous research, which tended to focus on specific instances of horizontal relations, neglecting the more holistic view. Thus, the typology proposed below will focus exclusively on horizontal relations. As has been argued in the introductory section, we believe that a systematic analysis of the types of relations that exist among objects of a map (i.e. horizontal relations) will be instrumental to the further development of more complex, contextual generalization techniques. Vertical and update relations are not addressed further in this paper.

Relations, Constraints and Measures

Together with the generalization algorithms, relations, constraints, and measures represent the fundamental parts of an automated generalization system. More specifically, the triplet relations-constraints-measures forms the basis for controlling the application of generalization algorithms, that is, the selection of appropriate generalization algorithms to remedy a given conflict situation, including the suitable parameter settings. While it should be clear what (generalization) algorithms do, it seems to be useful to define measures and constraints and explain their interaction with relations.

Cartographic *constraints* are used to formalize spatial and human requirements that a map or a cartographic map feature needs to fulfill (Beard 1991, Weibel and Dutton 1998). Examples are the minimum size constraint of an object (e.g. a building) or part of an object (e.g. a building wall), or the maximum displacement constraint to preserve the positional accuracy of a map object. Certain constraints may be termed 'hard constraints' (e.g. in generalization, a house must not change sides of the road along which it lies). Their evaluation will thus lead to a binary result (fulfilled / not fulfilled). Most constraints, however, will be 'soft constraints', meaning that slight violations may be tolerated. A constraint can be described by an appropriate *measure* that captures the property expressed by the constraint (e.g. the area of a building as a measure of the size constraint). The degree of violation of a constraint can then be evaluated by calculating the value for the associated measure and comparing that value to a target value that should be met for an optimal map at the target scale. The deviation of the actual and the target value will then yield a normalized 'severity' (or satisfaction, conversely) score expressing the degree of constraint violation (Ruas 1999, Barrault et al. 2001).

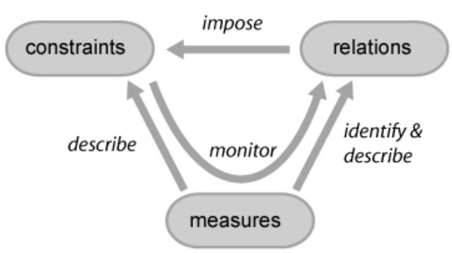

Figure 3. Interactions between constraints, measures and relations.

While the interactions between constraints and measures have been studied by various authors (e.g. Ruas and Plazanet 1996, Ruas 1999, Harrie 1999, Bard 2004), we would like to extend this to discuss the roles and interactions in the triangle of constraints, measures, and *relations*, as shown schematically in Figure 3. To illustrate our discussion, we will use the (simplified) example of a set of buildings that are aligned in a row, assuming that we would like to preserve this particular pattern in the generalization process. The spatial arrangement of the buildings can be seen as a relation of type 'alignment', where every building is related to the group making up the alignment. Within the alignment, further relations can be found, such as distance relations (expressing the distance of the buildings from each other), angle relations (expressing the angular deviation from the alignment axis), size relations (expressing the area of the buildings compared to each other), shape relations (expressing the similarity of building shapes), and semantic relations (expressing the similarity of the building types). To *describe and identify* these relations, appropriate measures are required. Identifying the complex relation 'alignment', for example, requires measuring whether the buildings are not located too far from each other (distance relation), whether they are sufficiently collinear (angle relation), whether they are similarly large or small, whether they are similarly shaped, and whether they belong to the same or similar building type. Once the relations have been established, they *impose* constraints on the generalization process, since one of the objectives of cartographic generalization is the preservation of structures and patterns represented in the relations. We have already mentioned above that the role of measures with respect to constraints is to *describe* constraints. Hence, since relations are imposed on the generalization process as constraints, measures are used by the constraints to *monitor* the evolution of the relations, and thus the constraint satisfaction in the course of the generalization process.

From the above discussion it becomes obvious that measures, constraints and relations are tightly linked to each other. Thus, existing classifications of measures and constraints will affect our typology of relations presented in the next section.

A Typology of Horizontal Relations

A General Structure Derived from Existing Classifications

A number of classifications of relations have been proposed in GIScience. Examples include the typology of topological relations by Egenhofer and Herring (1991) or the classification of spatial relations by Pullar and Egenhofer (1988), where the latter distinguish between direction relations (e.g. north, northeast), topological relations, comparative or ordinal relations (e.g. in, at), distance relations (e.g. far, near) and fuzzy relations (e.g. next, close). In the semantic domain, taxonomic (is-a) relations and partonomic (part-of) relations are commonly used in conceptual data modeling.

Although these classifications have proven to be very useful for GIScience applications in general, they are insufficient for cartographic purposes since they focus only on those relations that can be rigorously defined, leading to mutually exclusive and collectively exhaustive classifications. Maps, however, do more than simply portray an ideal world. Depending on their theme and purpose they attempt to graphically represent a portion of the real world with its associated ambiguities. Also, maps are made by humans for humans who have to rely on their visual perception to 'read' the messages conveyed by the graphics. Hence, it may be expected that a more comprehensive typology of relations among map objects has to go beyond rigorously definable types of relations, and include relations that are associated to 'human factors', including visual perception and partially also cognition. Note also that even in some of the more rigorous typologies of spatial relations, such as the one by Pullar and Egenhofer (1988), there exist types whose instantiation will depend on the cognitive experience, such as distance relations like far and near.

A typology of horizontal relations can be established in two ways, either from a functional perspective or the scope of usage. From both perspectives, several authors have already proposed classifications of map *constraints* relevant for generalization. The first classification, proposed by Beard (1991), was a functional typology and distinguished between graphical, structural, application, and procedural constraints. This original classification has been revised later by other authors for specific applications (Ruas and Plazanet 1996, Weibel and Dutton 1998, Harrie 1999, Galanda 2003). For instance, the typologies of Ruas and Plazanet (1996) and Harrie (1999) focused on the graphical aspects of map generalization. A constraint typology with respect to the scope of usage has been presented by Ruas (1999), distinguishing between macro level (entire dataset or object class), meso level (group of objects) and micro level (constraints associated with a single object).

In terms of existing typologies of *measures*, McGarigal (2002) has presented a typology organized with respect to the scope of usage of measures in landscape ecology. He distinguishes the scopes of patch, class and landscape. Here, patch metrics are applied to a region of relatively homogenous environmental conditions. Class metrics describe measures for all patches of one category, and landscape metrics are integrated over all patch categories of the entire dataset or selected frame. In landscape ecology, the metrics are also classified into non-spatial and spatial categories, where the first group is called composition metrics and the second spatial configuration metrics (Gustafson 1998, McGarigal 2002). Finally, a functional classification for cartometrics has been presented by Peter (2001). He organizes the metrics into (1) size, (2) distance and proximity, (3) shape, (4) topology, (5) density and distribution, (6) pattern and alignment, and (7) semantics.

Figure 4 shows the organization of the top-level categories of our typology. It represents a fusion of the functional typologies discussed above, focusing on the commonly used categories. ‘Geometric’ can be linked to the ‘graphical’ of Beard (1991) and Weibel and Dutton (1998) and also represents an aggregation of the first three types of Peter (2001). ‘Topological’, ‘semantic’ and ‘structural’ are categories used in basically all typologies (except the early attempt by Beard). ‘Statistics and density’ can be likened to the ‘density and distribution’ type of Peter (2001). The two types ‘application’ and ‘procedural’ by Beard only make sense when used with constraints, not relations, as relations describe states and not processes.

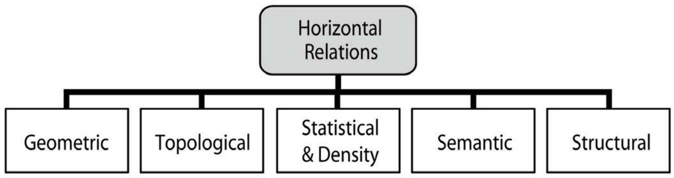

Figure 4. Typology of horizontal relations.

Methodology

To populate the typology, we used a two-pronged approach. On the one hand, we studied the literature on a) existing guidelines on topographic and thematic mapping; b) sets of constraints proposed for topographic and thematic maps; and c) measures used for the evaluation of constraints. On the other hand, we visually analyzed a number of topographical, geological and soil maps, as well as thematic atlas maps to identify relations. If available, we used pairs of maps showing the same area at different scales, to identify what steps the cartographers had carried out in the map generalization process, and thus gain an understanding of the influence of horizontal relations on generalization decisions. Overall, the maps covered a wide range of scales between 1:10,000 and 1:25,000,000.

Before proceeding with the presentation of the typology, two comments seem warranted. First, while we seek to develop a typology of horizontal relations that is as comprehensive as possible, we do not claim it to be exhaustive, for the very same reasons outlined in the preceding subsections, most notably the difficulty of achieving rigor. Second, we assume that the horizontal relations present in topographic maps form a subset of those existing in thematic maps. This assumption is supported by the observation that thematic maps often make use of base maps that are indeed topographic maps, as is the case in geological maps and soil maps.

A Set of Horizontal Relations

In the remainder of this section we present a set of relations that should define a foundation for the characterization of geographic data for automated map generalization. Some of the relations and properties of objects are well known and therefore need not be explained in detail, while others are briefly discussed. If applications of the corresponding relations have been described in the generalization literature, we will give at least one reference. Since measures are used to describe relations, we also will give references to those if available. We will make use of the classification of generalization operations proposed by

McMaster and Shea (1992) whenever we describe what operations may be supported by a particular type of horizontal relation.

Geometric Relations

Geometric relations originate from the geometric properties or the position of a map object. As shown in Figure 5, we make a basic distinction between geometric relations into *comparative relations* on the one hand and *direct relations* on the other. Comparative relations are established by comparing values of geometric properties – which are themselves unary relations – of real world objects or with idealized objects (thresholds), e.g. the size of an area or the length of a line. In contrast, direct relations express binary relations between objects, such as spatial distances or shape difference measures.

In our analysis of comparative and direct geometric relations, we identified four groups of geometric properties that describe a geographic object: *size*, *position*, *shape* and *orientation*. Most of these geometric properties and associated relations in Figure 5 are well known in GIScience and in map generalization. Thus, we refrain from going into much detail and point to the literature instead.

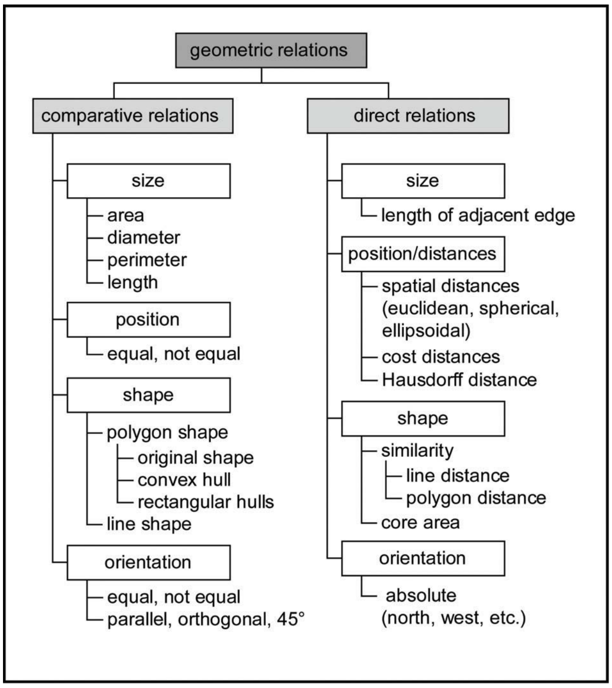

Figure 5. Geometric relations.

Size properties and relations – Area, diameter, perimeter and length are basic properties that describe the size of geometries. They have been used in generalization to evaluate constraints that describe the minimum size of a geometry or part of a geometry to be visible on the map. An application of size relations (comparing measured value to threshold value) is given in Regnauld et al. (1999), who present generalization algorithms to ensure the legibility of buildings in topographic maps. As one specific size relation, we want to mention *length of adjacent edges*, which measures the length of the common border between two polygons and serves as a basis for the *border length* index. The border length index is a structural relation useful to evaluate the similarity among categories such as soils (see Figure 14).

Position relations / distances – Distance relations are used in generalization to evaluate the proximity of map objects. Usually, distance relations are applied in map space to evaluate whether two objects can be visually separated, triggering generalization operations such as feature displacement. Alternatively, distances can be used in geographic space to form groups of objects (e.g. clusters of buildings that are close to each other). Finally, distance relations are also utilized in the so-called feature space, to identify objects with similar properties. Displacement algorithms to solve distance conflicts are described by Ruas (1999) and Bader et al. (2005). Approaches for the identification of building groups based on spatial proximity evaluation have been presented by Boffet (2001), Regnauld (2001) and Anders (2003). Note that most of these techniques use proximity-related supporting data structures, such as the Delaunay triangulation or Voronoi diagram to represent the distance relations.

Shape relations – There are diverse uses of comparative shape relations (e.g. comparing compactness and sinuosity values) and of direct shape relations (e.g. angular distance). They can be used (a) to describe visual similarity among objects or regions (e.g. for buildings, see Steiniger et al. 2008, Barr et al. 2004); (b) to evaluate whether geometric transformations such as smoothing, simplification or typification are necessary (e.g. for roads, see Plazanet et al. 1998); (c) to measure whether the shape deformation of a geometry is still acceptable when geometric transformations are applied (for buildings, see Bard 2004); and (d) to guide the selection of appropriate generalization algorithms (for roads, see Mustière et al. 2000).

For polygons and lines, such shape relations can not only be calculated for the original shape, but also for derived shapes, such as the convex hull and rectangular hulls (e.g. axes parallel envelope, minimum bounding rectangle). Since a large collection of shape measures for polygonal and line objects exists, we refer to the literature for more details. A comprehensive list of shape descriptors and other measures useful for generalization purposes is given in AGENT Consortium (1999). A further evaluation of polygonal shape indices has been presented by MacEachren (1985).

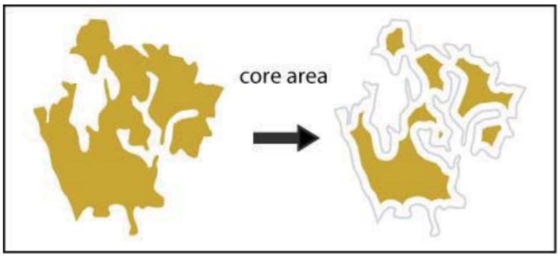

Figure 6. *Core Area* is calculated using an internal buffering operation. Data: Digital Chart of the World (DCW).

Core area (Gustafson 1998) is a specific shape relation listed in Figure 5 that will be explained in more detail. The measure is calculated using a negative buffer operation and returns a geometry (Figure 6). Core area does not reflect a relation to a specific map feature; instead it presents a relation of a polygon to its environment. In landscape ecology the index is used to define a core zone, where a species is assumed to exist with 100 % certainty. The area between core and polygon edge designates a transition zone between two species. Thus, the relation represents fuzziness, which is a common property for boundaries in a number of categorical map types (e.g. in soil maps). Another application of core area is its use as an indicator for a necessary geometry type change, that is, to decide whether a river polygon should be collapsed to a line symbol. McGarigal (2002) advocates that Core area integrates polygon size, shape, and edge effects into a single measure.

Orientation relations – Similar to shape relations, the relations among orientation of diverse objects can be used to form groups of objects. An application has been presented by Burghardt and Steiniger (2005) for the grouping of buildings by comparing the orientation of buildings to the orientation of nearby roads, in order to form alignment patterns. Orientation relations, however, are not only used to group objects. Absolute orientations (north, east, etc.) and relative orientations between objects (parallel, orthogonal, etc.) are often emphasized to highlight object relations with their neighborhood or to facilitate map legibility. Examples are given in the generalization text by Swiss Society of Cartography (SSC 2005). Measures to calculate the orientation of buildings are presented in Duchêne et al. (2003) and may serve as a basis to derive orientation measures for natural polygons.

To summarize, we showed that geometric relations are important in map generalization for four reasons. First, they are needed to evaluate whether geometric transformations of map objects are necessary to maintain the legibility of the map. Second, they help to calculate the degree of geometric transformation required to ensure map legibility. Third, they are used to evaluate whether a certain limit of deformation is exceeded. Finally, they are used to identify perceptually similar and close objects to detect more complex structures such as alignments. Thus, on the one hand geometric relations help to identify and manage generalization problems, while on the other hand they can be seen as building blocks for the recognition of perceptual patterns. Both issues are treated in more detail in the application example of island grouping and generalization presented in the following main section.

Topological Relations

In our analysis of the literature and maps we identified four types of topological relations: *intersection type*, *topological structure*, *neighborhood order* and the so-called *ring configuration* relation (see Figure 7). The essential purpose of these relations in map generalization is to prevent topological inconsistencies that are introduced in the generalization process and to preserve connectivity information. The four relation types will be explained below in more detail.

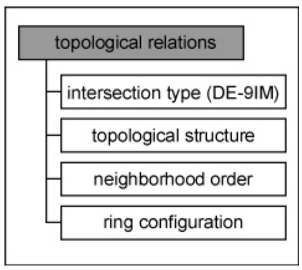

Figure 7. Topological relations.

Intersection type – To evaluate topological relations between two geometries, one needs to define a set of basic possible relations and describe how these can be determined. Such a set of basic relations has been proposed by Egenhofer and Herring (1991), Clementini et al. (1993) and others for the 2-dimensional case, and has evolved to a standard definition for GI systems in the OpenGeospatial Simple Features specification (OGC, 1999). The basic set (DE-9IM) in the OGC specification describes the following topological relations between two geometries: (1) disjoint, (2) touch, (3) cross, (4) within, (5) overlap, (6) contain, (7) intersect and (8) equal.

This set of primitive topological object relations is a necessary condition to describe the other three topological models below. Additionally the intersection type is directly utilized in generalization to check whether geometrical generalization operations introduced topological inconsistencies. For instance, following a displacement operation a river and a road may cross each other where they did not before the operation.

Topological structure – This relation type distinguishes between three structure models: island polygon, island cluster, and landscape mosaic (see Figure 8a). The naming of the structures *island polygon* and *landscape mosaic* is derived from the landscape ecology's perspective on patches (McGarigal 2002). The distinction of these three types is useful, on the one hand, to preserve the typical patch structure frequently found in polygonal maps (e.g. soil or geological maps), and on the other hand, to select and parameterize appropriate generalization algorithms. The latter purpose will be illustrated by an example.

The displacement model by Galanda and Weibel (2003) for the solution of proximity conflicts in polygonal maps requires the initialization of a deformation model. In this model, a polygon is either defined as rigid – and thus will be displaced as a whole – or the polygon outline is elastic and hence can be deformed. After analyzing the topological structure of the map and the size relations, small islands (e.g. polygon *P* in Figure 8a) and small island clusters are typically assigned a rigid outline. Thus, they will be displaced as a whole. In contrast large polygons, polygons that are part of a landscape mosaic (e.g. polygon *R* in Figure 8a) or large island clusters, will obtain an elastic outline in order to allow the resolution of proximity conflicts by partial deformation.

Neighborhood order – This topological index starts from a seed object (index = 0) and assigns every next neighbor visited an increasing order number (1, 2, …, *n*). An example is shown in Figure 8b where polygon A denotes the seed object. The order number is usually calculated by counting the minimum number of borders that have to be passed to move from the seed object to the current object. This index can

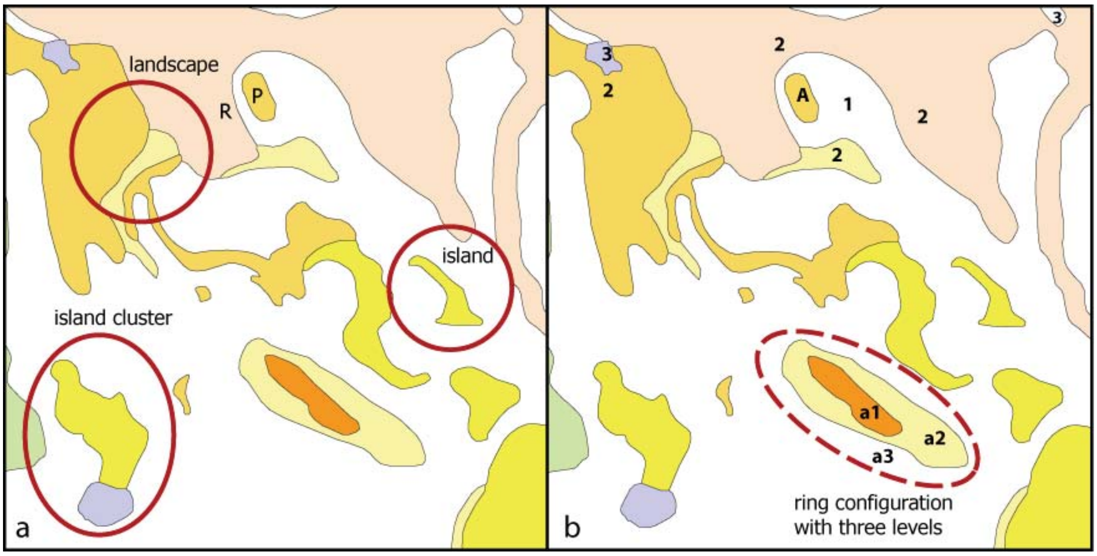

Figure 8. Topological relations. a) Circled in red are examples for the three *topological structure models*: island polygon, island cluster and landscape mosaic. b) Example of the *ring configuration*. Here, three ring levels a1, a2 and a3 (background polygon) exist. The *neighborhood order* is given for the island polygon denoted by A. The numbers 1, 2 and 3 refer to the order of topological neighborhood with respect to polygon A. Data: © FOWG.

not only be calculated for polygonal data but also for points and lines. For points, the Voronoi regions (de Berg et al. 1997) are calculated first and then the number of Voronoi edges are counted that need to be traversed to move from one point to another. For lines in a line network, the neighborhood index is obtained by counting the number of nodes visited traversing the network. Topological ordering is well known in GIS analysis and elsewhere and has been applied in map generalization. In a displacement model for buildings, for instance, Ai and van Oosterom (2002) use the index to calculate the level of motion propagation for neighboring buildings.

Ring configuration – This particular configuration, where several polygons enclose each other like the peels of an onion (Figure 8b), is typical for maps of discretized continua such as isarithm maps of temperature, heights fields, or snow depth. If only two polygons are involved, this relation is similar to the island structure mentioned above. As with all other topological relations, the usefulness of the ring configuration lies in being able to detect such patterns in order to preserve them in the generalization process.

Statistical and Density Relations

Although basic statistics and density relations are also used in topographic map generalization, the main source for the relations presented in this subsection has been the literature on thematic mapping, and more particularly pattern analysis in landscape ecology. Here, the so-called landscape metrics have been developed to describe the heterogeneity and fragmentation of a landscape. They are usually grouped into two types of metrics, which are the non-spatial composition indices and the spatial configuration metrics (Gustafson 1998). The latter type of landscape metrics will be presented in the subsection on Structural Relations due to its patch based, and not category based, computation. In our typology we will distinguish between four groups of indices. These are: *statistical base indices*, *area relations*, *category relations* and *diversity metrics* (Figure 9).

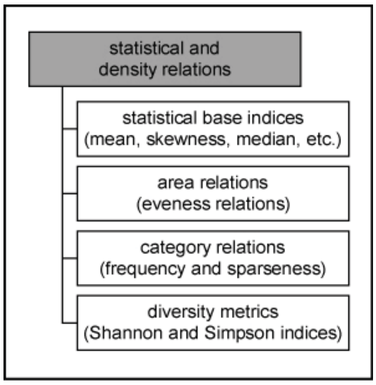

Figure 9. Statistical relations.

The use of these metrics has two main goals: 1) the preservation of overall map heterogeneity, which aims to maintain as much information as possible while ensuring a high level of map legibility, and 2) the detection of dominant or rare features. References to existing applications will be made in the detailed explanations below. A comment should be made on the naming: As most of the underlying measures and theory have been developed in landscape ecology, we retain the original terms ‘index’ and ‘metrics’.

Statistical base indices – With these indices, we address statistical distribution parameters such as the *n*-th order moments (sum, mean, variance, skewness, etc.) and statistical indices, e.g. median, argmin, argmax etc., described in standard books on statistics. They have been used already in topographical generalization to analyze, for instance, the homogeneity of city blocks or building groups (Boffet and Rocca Serra 2001). The analysis of the statistical distribution parameters is also used for the determination of classes for the display of a single phenomenon in simple thematic maps (e.g. population density maps). Such methods are described in Slocum (1999). An important role can be assigned to the analysis of attribute value distribution (variance) since it forms the basis for most clustering algorithms (Duda et al. 2001) for classifying thematic datasets.

Area relations – The indices of this group are also called evenness relations and describe areal ratios. Example indices are the *item area probability*, which describes the area ratio between the current polygon and all polygons of the same category, or the *evenness index* (McGarigal and Marks 1995), describing the area ratio between the polygons of one category to all polygons in the map or section. The area relations are useful for identifying rare categories in terms of occupied space and to measure the preservation of area ratios when geometric generalization operations are applied. For the latter case, a rather simple application is the black-to-white ratio, which is used e.g. in building generalization to determine the number of (enlarged) buildings to be retained in a building block (SCC 2005, Burghardt and Cecconi 2007). The ratio is based on the area that the buildings (black objects) will occupy on the target map, compared to the white space. This procedure should give the user a good impression of the settlement density, despite the condition that not all buildings can be displayed on the target map.

Category relations – Category related indices measure the frequency of occurrence and, hence, level of sparseness. The *relative patch richness* measures the number of categories in a map section and relates it to all existing categories (McGarigal and Marks 1995). Thus, the index describes local homogeneity. The other index in this group is *category probability*, relating the number of items of one category to all items. As far as we know no use has been made of these indices in map generalization. However, we suggest that the latter index is useful for detecting rare categories, whereas the relative patch richness index can be used to evaluate whether the local heterogeneity has been preserved after applying a reclassification operator.

Non-spatial diversity metrics – This group of metrics encompasses composite measures of evenness and richness (McGarigal 2002), which have been described in the two previous categories. The landscape metrics part of this group are, for instance, the *Shannon diversity index*, the *Shannon evenness index*, the modified *Simpson diversity index* and the modified *Simpson evenness index* (McGarigal and Marks 1995). These indices can be applied either to the whole map or to a map section. Both Shannon indices characterize the amount of information, the so-called *entropy*, a concept that originated in communication theory (Shannon and Weaver 1948). The original Simpson indices are not entropy measures; instead they can be seen as probability measures. According to McGarigal and Marks (1995) the *modified* Simpson and Shannon diversity indices are similar in many respects and have the same applicability for the characterization of landscapes.

A possible application of the Shannon diversity index in map generalization is to measure the loss of information resulting from the generalization process. In contrast, the Shannon evenness index can be useful for identifying dominant categories, since evenness is the complement to dominance (*evenness* = 1 - *dominance*; Gustafson 1998). A practical application of entropy measures to soil maps has been reported by Ibáñez et al. (1995) to assess pedodiversity (i.e. the variation of soil properties). According to Fuchs (2004), entropy measures are used as well by the German LGRB (State Office for Geosciences and Resources Brandenburg) to evaluate the quality of their soil maps, which have been derived through generalization processes. Finally, Bjørke (1996) proposed two applications of entropy measures, on the one hand for evaluating automated map design and on the other hand for eliminating point symbols while preserving point cluster structures (Bjørke and Myklebust 2001).

As a final comment in this subsection we have to admit that while we did advocate the use of metrics developed in landscape ecology for generalization purposes, no practical applications to generalization exist so far, to our knowledge, except for the non-spatial entropy-based measures. We clearly see a need of generalization research to evaluate the potential and expressiveness of such metrics.

Semantic Relations

The structural analysis, and with it the study of semantic relations, represents the first stage of map compilation. Especially if categorical maps are directly derived from GIS data or if for instance a small-scale soil map should be derived from a medium-scale soil map, then the number and structure of the categories needs to be defined. This differs from topographic map generalization, where the map content and classification schema are often clearly defined by the mapping authorities. In topographic maps, the classification usually differs only from country to country; for soil maps, on the other hand, the map legend units may differ from map sheet to map sheet. Therefore, the semantic analysis needs not only to address *priority relations* of categories and object groups, *resistance and attraction relations* between individual polygons, and *causal and logical relations* between classes (all of which can be found in topographic maps), one also needs to address *similarity relations* to define the legend units of thematic maps (Figure 10).

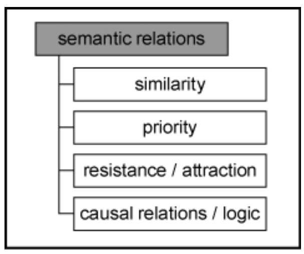

Figure 10. Semantic relations.

Semantic similarity relations – As it has been emphasized above, similarity relations are needed to assign map objects to the categories of the new map. If the classes are not known beforehand, they have to be inferred from the data. Every object is first described by several properties that characterize it and may help to distinguish it from others. For instance, a building can be described by its area, squareness and perimeter, that is, the geometric properties discussed in a previous section. These properties span an *n*-dimensional *feature space* (n denotes the number of properties). In Figure 11, such a feature space spanned by 10 properties of buildings is shown (but transformed to a 2-D space for visualization purposes). Every dot in this image represents a building in the feature space, whereby the position is defined by the values of its geometric properties. The similarity between two buildings can now be obtained by measuring the distance that separates them in feature space. Buildings with similar properties will be located close together. If we would like to classify the buildings into categories that represent similar building types (and thus also similar urban settlement structures), we may apply so called unsupervised pattern classification methods such as clustering (Duda et al. 2000). Such methods will probably identify three building structure categories in our example, corresponding to the three point clouds (clusters) shown in Figure 11. In contrast to the similarity between two individual buildings, the similarity between two categories is not only expressed by the distance in the feature space, but also represented by the distance and a probability model that accounts for the shape of the point cloud making up the categories. Were we to use the pure distances only, as the semi-circle around the center of category 1 indicates, then the objects of category 2 would belong to category 1.

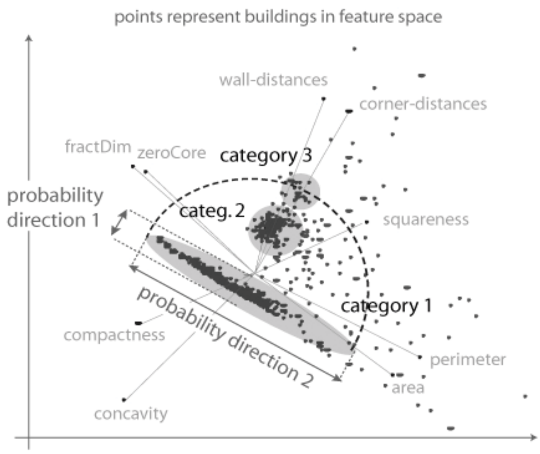

Figure 11. Buildings described by geometric properties depicted in feature space. The buildings form 3 natural categories (clusters). The definition of *similarity* in feature space encompasses distance *and* probability. Otherwise the objects of category 2 would belong to category 1.

Sometimes, categories are known in advance and the task will then consist of assigning new observations to these known prototypes. Let's assume that for the purposes of a planning map, the prototypical categories 'inner city', 'urban', 'suburban', 'industrial' and 'rural' have been defined to classify a study area into zones of different structure types based on the characteristics of the buildings they contain. We can then again start by characterizing the buildings by means of geometric properties such as area, squareness, perimeter etc. Every prototypical category (inner city, rural area, etc.) is then defined by selecting a set of representative buildings for every category (i.e. a training sample). These representative buildings can then be used in classification methods, such as discriminant analysis, to assign the remaining buildings to the prototype classes (Duda et al. 2001). Since we use prior knowledge (i.e. the training samples) the classification is called supervised. The similarity is again defined by distances in the features space.

Besides using distance in feature space, other methods are possible to define semantic similarity and to determine categories based on similarity. A second approach is to establish classification rules based on object properties. These rules are then used to assign objects to categories. To stay with the above example of settlement classification, for instance, all very large buildings may be defined as industrial and separated from the rest. The remaining buildings are then further analyzed to identify buildings that are alone within a 100 m buffer. These single buildings are now separated and defined as rural buildings, while the remaining buildings are again analyzed further. This approach results in what is usually called a decision tree (Duda et al. 2001). The similarity in this case is expressed by the rules.

A third approach to express similarity can be used if the data are already organized in a set of categories and this set should be reduced. For instance, if the five categories of the above planning map should be reduced to the two categories 'rural' and 'urban', then the similarity needs to be defined by the user. This is preferably done by assignment rules that relate each category to its super-category.

Applications of similarity analysis have been presented by several authors for map generalization. More generally, Bregt and Bulens (1996) discuss three approaches to aggregate soil areas using a classification hierarchy defined by an expert, the border–length index (see the description of configuration metrics in the following sub section) and a self-developed similarity index. Based on this work, van Smaalen (2003) later developed an approach to derive an aggregation schema for the land use layer of topographic maps. Fuchs (2002) used properties of soil patches as input values for a cluster analysis to generate a new set of soil categories. Steiniger et al. (2008) presents a discriminant analysis approach for the classification of urban blocks into predefined urban structure classes based on representative buildings. Approaches to derive rules for a decision tree to classify roads for generalization purposes are reported by Mustière et al. (2000).

Priority relations – Like similarity relations, these relations focus on the category level, but additionally also on the object group level. Priority is used in the generalization process to give more importance to some special object class or category than to others. For instance, in topographic maps roads have a higher importance than buildings. Thus, roads push buildings away if they are widened for visualization purposes. The priority of roads over buildings also implies that roads are generalized first, while buildings are only dealt with later. In thematic maps, the theme or purpose of the map basically decides on the priorities of object classes or categories, respectively. For instance, in a vegetation map rare plant societies are emphasized over other categories even if the corresponding polygons are too small to be displayable. Explicit modeling of priority for object groups over non-grouped objects has already been realized. This was shown by Gaffuri and Trévisan (2004) for the preservation of building alignments.

Resistance and attraction – The resistance and attraction relations focus on the individual object level. They define whether neighboring polygons are aggregation candidates or not. The resistance relations can be either defined by the user or calculated as a compound index based on semantic similarity, class priority and/or statistical relations. The relations are, for instance, evaluated when the generalization system needs information about whether it may aggregate two forest polygons across a small area of another land use type. Here the resistance relation will probably return a positive value (attraction) if the small area is grassland. But the aggregation would be rejected if the area between the forest polygons is a river (resistance).

Causal relations – Such relations describe dependencies between categories. Causal relations are used if map features should be eliminated or classes aggregated during the generalization process. An example for the use of causal relations has been reported by Duchêne (2004) for topographic maps. In her generalization system, the categories of road and buildings have been linked with a causal relation. In the case that a road is deleted, the system searches for nearby buildings that would lose their connection to the road network. If such buildings are found, then the system has two choices. Either it deletes the buildings as well, or it restores the road if one building is marked as an important one (e.g. a hotel).

Structural Relations

As the word 'structure' suggests, the relations of this group should denote types of structural patterns that are perceived in maps. In this sense, most of the relations discussed in this subsection are linked to human perception and cognition. We have identified six relation types as being part of this group: the *background-foreground relation*, *generating process*, *orientation patterns*, *spatial configuration metrics*, *macro structures* and *meso structures* (Figure 12). Apart from the background-foreground relation, the relations of this group should be identified in maps before the generalization itself starts to be able to preserve important patterns during map generalization.

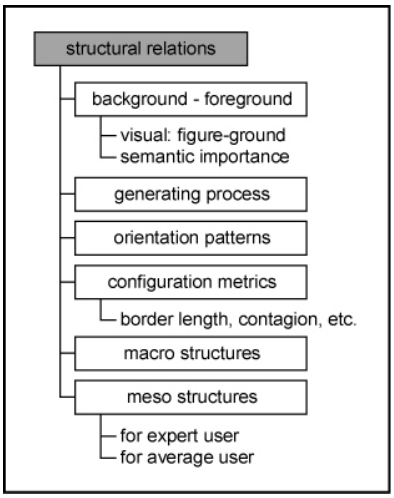

Figure 12. Structural relations.

Background-foreground relation – With this relation type, we want to ensure that problems can be addressed that concern the definition of a visual order in maps. Therefore, two issues must be considered: 1) the elimination of figure-ground effects (Dent 1999), which can be provoked by an unskillful choice of colors and lead to a wrong user perception of the map content, and 2) the agreement between semantic importance of an object class (given by map purpose) and its visual weight. For instance, a disagreement exists if roads in a topographic map are overlapped by forest polygons. Research in automated map generalization has paid only scant attention to these figure-ground problems, which we think is due to two reasons. On the one hand, the assignment of visual weight is not a problem in topographic map generalization since the symbols, colors and the order of the thematic layers of topographic maps are usually fixed and appropriately defined. On the other hand, despite some advances, such as the work by Chesneau et al. (2005) on automated color contrast enhancement, research in thematic map generalization is still far from being able to establish a ready-to-go map production system. Thus, it can be assumed that there always exists some manual post-processing stage in which a designer or cartographer can revise figure-ground problems and assign the correct visual weight.

Generating process – This relation should describe whether a map reader may gain the visual impression of the underlying process that generated the displayed real world objects. We propose to distinguish three types: *without structure*, *artificial structure* and *natural structure*. The characterization should be applied to three scopes: a) on the complete map or a map section, b) on groups of map objects and c) on the object and its parts. In the upper image of Figure 13, examples for an artificial and a natural structure of soil site borders are shown (type c). On the object level, shape measures such as sinuosity and squareness may be helpful to identify the type of the generating process relation. However, apart from early work (Buttenfield 1985), measures have not yet been developed sufficiently to reliably detect such structural relations. The use of configuration metrics from landscape ecology (see following section) should be evaluated for use on entire maps, map sections, or at group level. For point distributions, the well known nearest neighbor index (Haggett, 2001) can be applied.

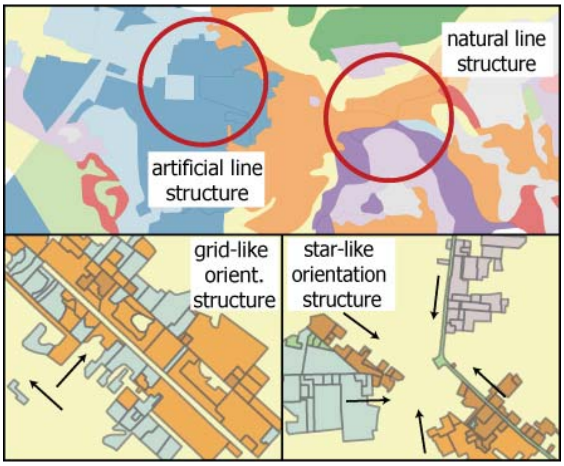

Figure 13. *Structural relations* and properties. The upper picture shows artificial and natural polygon structures from a German soil map. The lower pictures present two examples of orientation patterns in a land-use dataset from New Jersey. Here, the orientation patterns are induced by the road network. Data: © LGRB, NJDEP.

Orientation patterns – This relation type corresponds to the extension of the simple orientation relation of two objects (cf. geometric relations) to more complex patterns. Examples of such complex configurations include star-like patterns and grid structures, shown in Figure 13, as well as circular arrangements. Orientation patterns of road networks have been described by Zhang (2004) and Heinzle et al. (2006) for generalization purposes and by Marshall (2005) for transportation analysis. Heinzle et al. (2006) also describes a method to detect circular road patterns.

Spatial Configuration metrics – Four different measures belong to the group of these spatial metrics, quantifying the configuration and fragmentation of a landscape. These measures are the *border length index*, *contagion*, *interspersion and juxtaposition index* (IJI) and *lacunarity analysis*. Typically, the configuration metrics are based on a matrix of pair wise adjacencies between all patch types. The elements of such a matrix hold the proportions of the edges in each pair wise combination as it is shown in Figure 14 (McGarigal 2002). While the border length index and IJI can be applied to vector data, the contagion index (Li and Reynolds 1993) and the lacunarity analysis (Plotnick et al. 1996) can be applied to raster data only. Note that lacunarity analysis differs from the other indices in that it is a multi-scale method with a binary

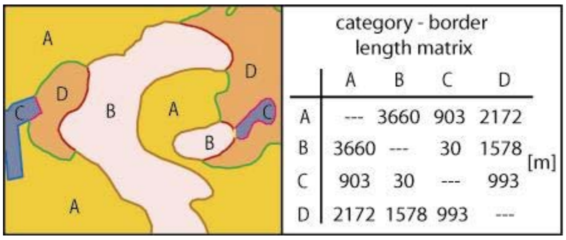

Figure 14. A section of a landscape and its configuration described by the category-border length matrix. The matrix is used for different *spatial configuration* indices. Data: © LGRB.

response. In general, we suggest using these metrics to measure the change of fragmentation before and after generalization to quantify the changes. Since no experiences exist with these measures in map generalization, however, research is required to evaluate their explanatory power. Despite that, one concrete application of the border length index has been reported by Fuchs (2002). The index gives a probability for the common appearance of two categories and consequently provides a sort of similarity measure. Fuchs (2002) used this measure of similarity as one criterion to obtain a reduced set of legend units for the generalization of a soil map. Apart from the work by Fuchs (2002), it is also worth mentioning that the border length index is implemented in sliver removal procedures available in commercial GIS software (e.g. ESRI ArcGIS, eliminate tool). Here, sliver polygons are merged with the neighboring polygon with which they share the longest common edge.

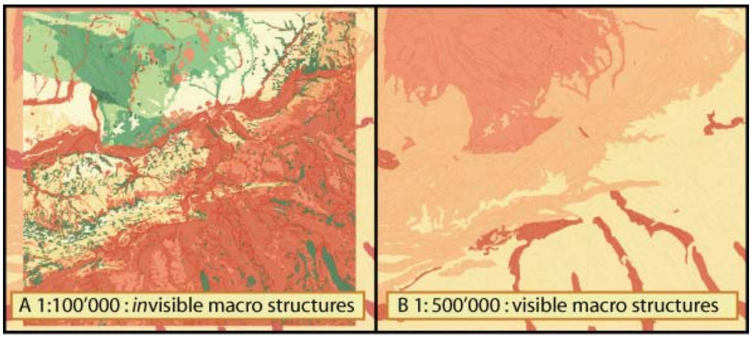

Figure 15. *Macro Structures*. Macro structures are concealed in the original map scale if the reader has no information about them, but they are clearly visible at smaller scales. In picture B a geological macro structure extends from SW to NE. Maps not shown to scale. Data: © FOWG.

Macro structures – These types of patterns can only be recognized if the map reader has particular information about them. Macro structures are not directly manifested and visible on a map of a given scale. Rather, they relate to a different (macro scale) level and resolution than the current map. An example is given in Figure 15, which shows geologic patterns of the Black Forest north of the Swiss-German border. They can hardly be perceived in the map at scale 1:100,000 (left) but they become obvious in the map at scale 1:500,000 (right). A detection of such structures in high-resolution map data by pattern recognition methods is difficult to accomplish, since the granularity is too high ('one cannot see the forest for the trees'). Nevertheless, the influence of such large structures on map design is high since cartographers use them as structuring components. Consequently, a person who knows about such macro structures will tend to abstract them, even on large scale maps. Attempts to address the usage of information on macro structures in automated generalization have not yet been reported.

Meso structures – In contrast to the macro structures, this last type of the structural relations covers visible and detectable patterns. Examples of meso structures are given in Figure 2 (left), showing alignments of soil patches of the same category. For meso structures, a differentiation can be made into visual patterns that are obvious to every map-reader (e.g. four aligned lakes) and thematic patterns, only obvious to the experts familiar with the particular topic. The structures visible to every map reader will be perceptual patterns, which have been described by Wertheimer (1924) in his '*Laws of organization in perceptual form*', and correspond only to a lesser degree to patterns formed by the reader's background knowledge. How perceptual patterns are formed is briefly discussed in the next section (cf. Figure 18). Besides the previous distinction into expert and non-expert patterns, a classification of meso structures into structures composed of entities of a single or of multiple object classes, respectively, can be made. Furthermore, a sub-classification is possible by consideration of the shape of a pattern, whereby *parallel* or *curved* alignments, *clusters* or *layers* can be distinguished.

Approaches reported for the recognition and preservation of meso structures focus, in most cases, on the analysis of building structures in topographic maps. Several researchers presented methods to detect either building alignments (Christophe and Ruas 2002) or other building groups perceived as "intuitive" (Regnauld 2001, Boffet 2001, Anders 2003). Another typical example for the consideration of meso structures in topographic maps is the recognition of major road or water network structures. The detection methods are often based on the perceptual principle of good continuity (Wertheimer 1923, Thomson and Richardson 1999), but other methods, such as traffic simulation analysis in the case of road networks, have also been used (Ruas and Morisset 1997). As the final example of meso structure recognition, we like to refer to Downs and Mackaness (2002). They identify fault line structures in geologic maps to preserve them during the generalization process. Further meso structures are discussed in the generalization book of the Swiss Society of Cartography (SSC 2005) for the case of topographic maps.

Utilizing Relations to Characterize a Group of Islands

At the beginning of our research and of this paper we have set out the overall goal that the pro-posed typology should help to identify relations to support the generalization of topographic and thematic maps. We will demonstrate this on a concrete application example. The case we have chosen deals with the generalization of a group of islands. The problem of island generalization has been selected for several reasons. First, islands need to be generalized for thematic and topographic maps, although the particular goals and constraints might be different. Second, it is a simple example in that we need to consider only one object class and only one geometry type (polygons). This has the effect that not all generalization operations are applicable, and relations between object classes do not have to be considered. However third, and perhaps most importantly, it is straightforward to highlight the necessity of preserving perceptual patterns (i.e. the meso structures) even with this relatively limited example.

The island data that we use in the example are extracted from the ESRI Data & Maps media kit, and are part of an archipelago in the Baltic Sea. More precisely, the islands are located between the Åland Islands and the Finnish southwest coast, as can be seen in Figure 16. The archipelago, formed during the ice age, consists of so-called skerries (small rocky islands too small to be populated) and larger islands with diameters up to a few kilometers. The resolution of the map data corresponds to a nominal scale of roughly 1:350,000.

To our knowledge only two previous studies can be directly related to the generalization of islands. Both studies, in fact, use lakes rather than islands, yet we assume islands and lakes to be structurally similar for the purposes of generalization. The first study is by Bertin (1983), who describes a manual and stepwise approach for generalizing clusters of small lakes while preserving the spatial and structural configuration of the lakes. In the second study, Müller and Wang (1992) present an algorithm for the generalization of area patches exemplified on lakes (Bertin's lakes, as a matter of fact). They note, however, that their implementation was not able to preserve archipelago structures.

Cartographic Constraints for Island Generalization

Before we start to work through the list of relations relevant for island generalization, it is worth discussing which constraints provoke changes to the island data. There are, in general, two reasons why data are generalized. On the one hand, we like to obtain a legible map when the map scale is reduced. On the other hand, we may wish to reduce the amount of data for storage reasons or data transfer reasons (e.g. in web mapping). Galanda (2003) has presented a list of cartographic constraints for the generalization of polygons. An analysis of Galanda's list with respect to our island data delivered a set of five applicable active constraints. The group of so-called *active* constraints are the ones that try to fulfill the requirements of map legibility and low data volume. These constraints acting on the island map should ensure the following goals:

- C1: an appropriate distance between consecutive vertices on the polygon outlines to reduce data volume;
- C2: a minimum width of an island (or parts of it, e.g. bays or headlands) to be visible on the map;
- C3: an appropriate outline granularity, e.g. delete imperceptible bays or headlands;
- C4: the minimum size of an island to be perceptible in terms of the area; and
- C5: the good visual separability of nearby islands.

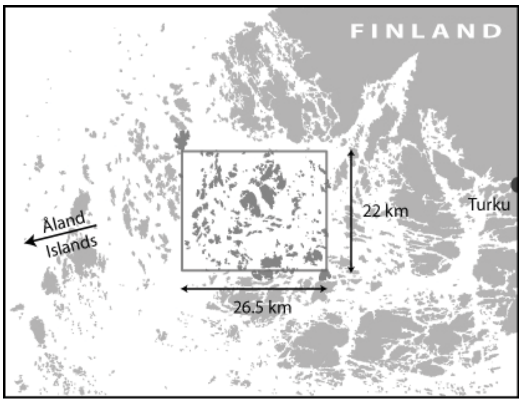

Figure 16. The box covers the islands data set used for the example of this Section. The islands are part of an large archipelago south west of Finland. Data ® by ESRI.

All other constraints applicable to islands enumerated by Galanda (2003) are *defensive* constraints. That is, they are used to prevent strong changes of an island's position or the distortion of an island's shape and to preserve the spatial configuration.

Evaluating the Relations for Island Characterization

We will now organize the relations of our typology into four groups. The first group, with which we will start, includes the non applicable relations. The remaining three groups are those that are relevant to our problem: Relations that help to evaluate active constraints; relations that can be assigned to defensive constraints; and relations that support the selection of operators and algorithms. The resulting classification is summarized in Figure 17, with relevant relation types highlighted in gray.

Non applicable relations – Eight relation types have been identified to be not applicable to islands. From the topological group, these are the ring configuration (no concentric polygons can be found), neighborhood order (since islands are disjoint), and topological structures (again, since islands are disjoint). Similarity, causal relations, categorical relations, as well as the diversity metrics, are not applicable because we have only one object class. Background-foreground relations do not play a role if the islands and the sea are assigned colors with respect to the map purpose and cartographic tradition.

Relations supporting active constraints – Only three types of relations induce generalization processes of a map. They all belong to the group of geometric relations. The size relations are used to evaluate the constraints C1 (vertex distance), C2 (minimum width) and C4 (minimum size). The position relations are used to evaluate whether two islands can visually be separated (constraint C5). The shape relations, e.g. in the form of a bend analysis (Plazanet et al. 1998), will help to evaluate the granularity constraint (C3).

Relations supporting defensive constraints – Most of the listed relations can be used for the defensive constraints. We will start our explanations with the geometric and topological relations and will then move on to the structural relations, since knowing the latter will be important for the details of other relations.

a) Geometric and topological relations: We have previously named the size, position and shape relations as relations that support the evaluation of active constraints. Similarly, they can also be used to

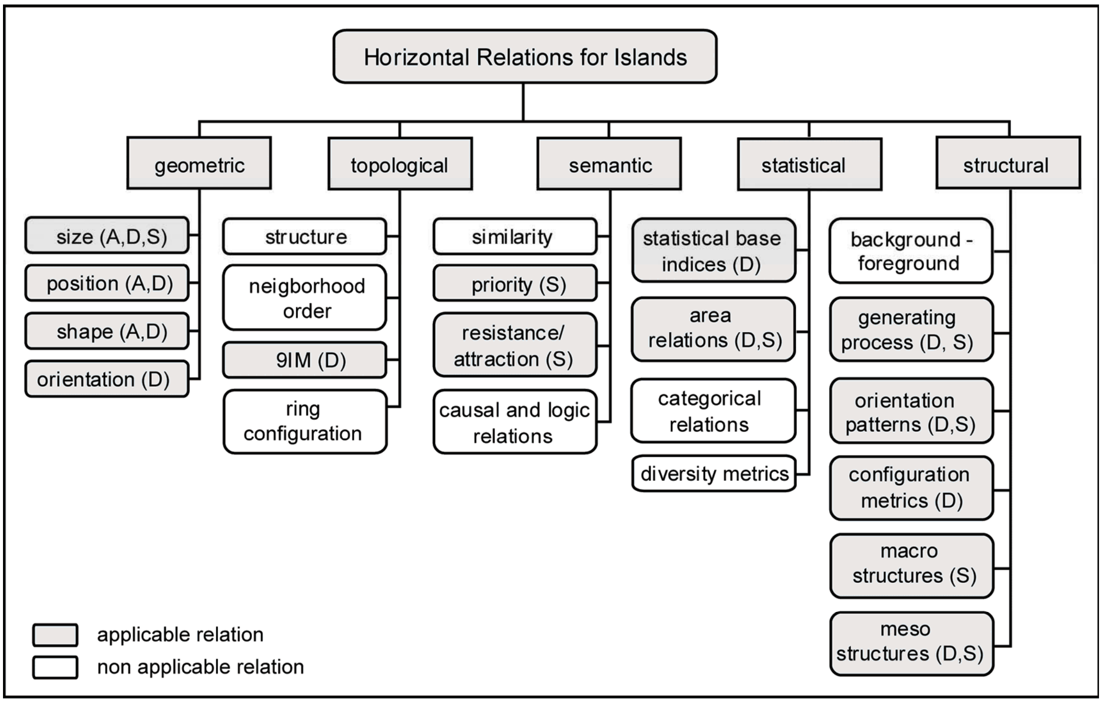

Figure 17. Applicability of horizontal relations to island generalization. A, D and S denote whether a relation is useful for **A**ctive constraints, **D**efensive constraints or operator and algorithm **S**election.

evaluate the effect of geometric transformations, e.g. displacement, enlargement or smoothing, and subsequently can help to identify excessive deformations. This does not only hold for size, position and shape, but also for the orientation relation and the 9IM relation. The orientation relation is necessary to evaluate whether absolute orientation and relative orientations have been changed in an unacceptable manner during generalization. The 9IM relation specifically serves the purpose of detecting cases where operations involving displacement either led to an overlap of islands, or led to a merger of two island groups that were previously considered as perceptually distinct.

b) Structural relations: Considering the applicability of the structural relations for defensive constraints and island generalization, we may identify four useful relations. The generating process should help to identify generalization operations that destroy patterns on two levels. On the global level, the distribution of islands may change from a natural structure to a more undesirable ordered structure. On the detailed level (i.e. object level), generalization operations may change the outline of islands from a natural smoothness to an artificial straightness or vice versa for port areas. Meso structures are a second useful relation. They describe natural, perceptual groupings of islands, which have to be identified to either preserve them during generalization, or even to emphasize them. To give a concrete example, we have marked such 'perceptual groups' within the islands groups in Figure 18. These groups have been identified in a pencil-and-paper experiment described in Steiniger et al. (2006). Based on these experimental results, Steiniger et al. (2006) could show that Wertheimer's (1923) "laws of organization in perceptual forms" (i.e. the principles of Gestalt theory) can be used to describe perceptual groupings of islands. For instance, the large groups in Figure 18 formed by people are based on Wertheimer's Gestalt principle of spatial proximity. In contrast, the smaller groups must be described not only by the spatial proximity principle but also by the principle of similarity of island shape, orientation and size, and the principle of dominance of a large island in a smaller group.

For the automated recognition of the large island groups identified visually by humans, Steiniger et al. (2006) have presented algorithms that formalize Wertheimers principles by means of a set of horizontal relations and, more specifically, using the geometric relations including distance, shape and orientation. The third applicable relation is the orientation pattern, which can be used to evaluate the defensive constraints. An orientation pattern that can be found in the example of Figure 18 is the meso structure G1 in the lower left corner, showing a banana-shaped orientation. Other meso structures, such as the group G2, exhibit a straight orientation to north. The spatial configuration relation is the fourth relation type, which supports the evaluation of defensive constraints. With the configuration metrics, excessive changes in the land-sea configuration could be detected.

c) Statistical relations: If meso structures are found, then two statistical relations become relevant to describe them and subsequently support the defensive constraints. On the one hand, the basic statistical parameters can be used to describe the group of islands in terms of their area, distribution, extent and position properties. This can be done before and after generalization. On the other hand, the area relation should be used to evaluate whether the black-to-white ratio (ratio of the area covered by the islands to the area of the background) has changed for the map partition occupied by the particular island group. Both statistical relations and the spatial configuration relation require the specification of limits for changes that are still considered acceptable. If these thresholds are exceeded, then the generalization actions should be rolled back and adjusted.

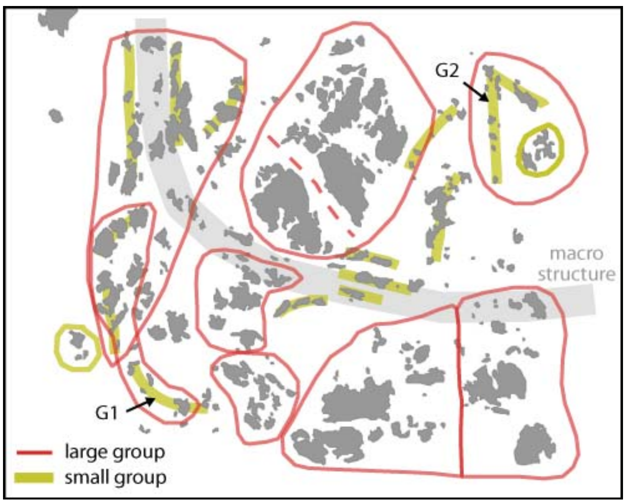

Figure 18. Meso structures in the archipelago identified by participants in a pencil-and-paper experiment.

Relations supporting algorithm selection – An important utilization of the above relations is that their identification and characterization can inform the selection of generalization algorithms. As an example, one will usually not apply a smoothing operator to the part of an island outline that represents the docks of a port. For macro structures, the case is very similar. An example of a macro structure is illustrated in Figure 18. The structure represents a curved arrangement of islands leading from north to east. It is difficult to see in Figure 18, but can be recognized more easily when the view is extended to a larger area of the archipelago as shown in Figure 16. A macro structure can form a constraining generalization element that will force the algorithms working on a more detailed scale to emphasize this pattern.

If a separation constraint C5 is violated, then the area relation (statistical) can be used to support algorithm selection. For instance, if the island density is very high, as is the case in the middle of the large cluster to the north close to the mainland in Figure 16, then we have to use typification operations instead of displacement operations, because there is no space to displace all islands without removing some. Another relation that may be used to support the selection of an appropriate displacement algorithm is the size relation (geometric, comparative). For example, if a small island is located too close to a large neighboring island, then we need to find a solution by using displacement operations. If one considers the large island as a mainland object and the small island as an island object, then we will only displace the small island while fixing the large island's position and making the boundaries of both islands rigid.

Two relations which support algorithm selection are left to discuss. These are the priority relation and resistance/attraction relation. Priority is used to enforce that island groups that have been detected are preferred over other islands that are not part of any structure, and preserved in displacement, amalgamation or elimination operations. The use of the resistance relation may be explained if we assume that additional road data are available. Here the resistance relation may allow a merging operation if two islands are connected by a bridge. In contrast it will reject merging proposals if the islands are not connected by transportation lines.

Discussion

The discussion of the previous section has shown how horizontal relations can be used to formalize and evaluate constraints and to support algorithm selection for a specific example. We hope to have thus clarified the utility of the proposed typology. However, it is still largely an open issue how we can 'quantify' the relations themselves. This problem and related other issues that should be addressed in future research are discussed in this section.

A general schema for the utilization of relations in cartographic generalization can be seen to consist of five stages, as shown in Figure 19. In the first stage, relations are identified that may exist in a data set, with a focus on the relations that need to be preserved and should be emphasized. Here, the presented typology can serve as an initial check list on what kinds of relations may exist.

The second step aims to formalize the relations, that is, describe the elements of the relations in a sufficiently formal way so that rules or algorithms for the detection of relations can be developed in the subsequent step. For many of the relation types, the formalization can readily build on the literature cited in this article. This holds particularly for the relation types that are of a more generic nature, including the geometric, topological, and statistical relations. Semantic and structural relations, on the other hand, are often more specifically linked to the characteristics of the given object classes and map themes.

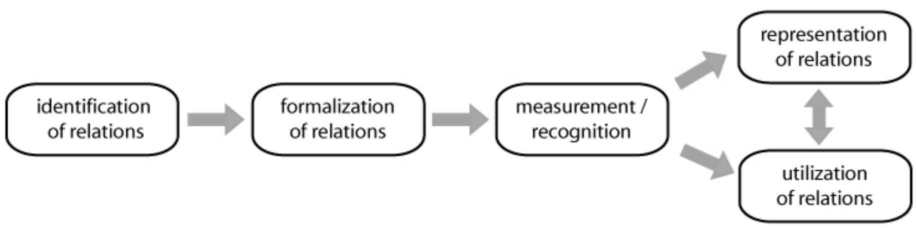

Figure 19. Utilization of relations.

Thus, while it is perhaps possible to benefit from experiences reported in the literature, the formalization has to be specifically adapted to each particular case. For instance, let's assume that visual exploration of a series of soil maps has established meso structures that relate gravel soils to river beds. We can then try to describe that type of meso structure by means of geometric relations, e.g. both objects seem to always have a similar orientation of the polygon segments involved, and topological relations, e.g. the gravel soil is adjacent to or overlapping the river bed. This formalization will help us to later develop, in the third stage, measures and pattern recognition algorithms for the more complex relations. Note also that the formalization step can be assisted by a variety of knowledge acquisition techniques, such as interviews with experts and observation of experts, as well as the pencil-and-paper exercises that were used in the island grouping example discussed in the previous section (Steiniger et al. 2006).

The third step consists of transforming the formalization of relations into actual rules and/or algorithms for the measurement and recognition of the corresponding relations. Again, we suggest that the above review of our typology of horizontal relations has provided useful links to the pertinent literature. Indeed, a plenitude of measures and algorithms exists that might be used to implement the recognition of relevant relations. Thus, as it has been pointed out in the discussion of landscape metrics, often the real problem will not be to find indices in the literature that can potentially describe a particular relation or measure a particular property of an object. Rather, the difficulty will be to identify whether the measure does exactly describe what we want it to describe. Linked to that is the problem of interpreting the values that are delivered by the measures, in order to make qualitative inferences from quantitative values. Apart from these two issues, the measurement/recognition stage should also address a further problem that arises if several measures are required in association to describe complex relations, such as perceptual meso structures. In this case we need to ensure that the various metrics involved do indeed measure different object properties. As an example for the necessity of an evaluation of measures that can be found in the literature, we refer to the study by Riitters et al. (1995). They evaluated the (dis-)similarity of 55 measures commonly used in landscape ecology by correlation analysis and factor analysis. 29 measures (i.e. more than half the measures) could be discarded preceding the factor analysis after a simple correlation analysis had established very high correlation coefficients ($r > 0.9$).

Once the measures and structure recognition methods have been developed and applied, then the fourth step involves the representation and storage of the relations found. Possible representations to store horizontal relations have been presented in Neun and Steiniger (2005) and Neun et al. (2006) ranging from the option to save values as simple attributes in tables, over relation matrices for class dependencies, to more complex data structures, such as triangulations and other graph data structures. In essence, the relevant data structures for representing horizontal relations are well known in the computing literature and will not go beyond graphs. The precise method of implementation, however, may depend on the specific case at hand, including algorithmic requirements such as space efficiency and computational efficiency.

The final step in the chain focuses on the utilization of horizontal relations. Application scenarios need to be developed for the horizontal relations, with a focus on the interaction between relations and constraints, as shown for the island example in the previous section. These scenarios should cover three aspects of the utilization of horizontal relations. First, constraints should be defined from the identified relations, such as the specific gravel soil-river relation. Second, the relations should be linked to established generic constraints to support the constraint evaluation for specific object classes in the generalization process. Finally, the third usage of relations is to develop rules for the selection of generalization operations and algorithms based on the information provided by the relations.

Conclusion

In proposing our typology of horizontal relations for thematic and topographic maps, we hope to strengthen research on an important part of the cartographic research agenda, automated generalization. We have shown in our example of island generalization how horizontal relations can be used to characterize map data, support the detection of conflicts, and assist in the choice of generalization operations appropriate for the resolution of these conflicts. Furthermore we deem the typology crucial for the development of more and better generalization algorithms that take into consideration the context of map objects and that are able to act over multiple object classes, rather than being restricted to a single object class, as is still frequently the case for existing generalization algorithms. However, the island generalization example was a conceptual one and has only partially been implemented. In order to accomplish the full task, many further problems will need to be solved. We have addressed some of these open issues in the discussion of the preceding section. Beyond that, a full scale solution will also have to link the various elements – constraints, measures, relations, and algorithms – together in a comprehensive system that is capable of controlling their interaction in the generalization process. Such systems have been reported in the literature, albeit so far only for specific generalization problems, as exemplified by the AGENT system for the generalization of urban zones in topographic maps (Barrault et al. 2001, http://agent.ign.fr).

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B. Research Paper 2

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An Approach for the Classification of Urban Building Structures Based on Discriminant Analysis Techniques

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Abstract

Recognition of urban structures is of interest in cartography and urban modelling. While a broad range of typologies of urban patterns have been published in the last century, only little research on the automated recognition of such structures exists. This work presents a sample based approach for the recognition of five types of urban structures: (1) inner city areas, (2) industrial and commercial areas, (3) urban areas, (4) suburban areas and (5) rural areas. The classification approach is based only on the characterisation of building geometries with morphological measures derived from perceptual principles of Gestalt psychology. Thereby, size, shape and density of buildings are evaluated. After defining the research questions we develop the classification methodology and evaluate the approach with respect to several aspects. The experiments focus on the impact of different classification algorithms, correlations and contributions of measures, parameterisation of buffer based indices, and mode filtering. In addition to that, we investigate the influence of scale and regional factors. The results show that the chosen approach is generally successful. It turns out that scale, algorithm parameterisation, and regional heterogeneity of building structures substantially influence the classification performance.

1. Introduction

Topographic maps at medium scale (1:50,000 - 1:100,000) and derived maps for urban planning often emphasise urban structures. The visualisation of such built-up area structures as inner city or industrial districts should support on the one hand map reading and on the other hand initial decision processes in planning. For instance the German topographic regional map (Topographische Gebietskarte, 1:100,000) distinguishes between four built-up structures: dense building areas, low density building areas, industrial and business districts, and single buildings. The visualisation for the first three types is done by coloured tints and single buildings are drawn by their outline. In contrast, French large scale maps of scale 1:25,000 display the industrial and residential buildings in different colours of the single building.
Our aim is to identify such different urban structure types using pattern recognition techniques. To render the approach simple in terms of data requirements the pattern detection should be based solely on the geometry of buildings, which assumes a perceptual coherence of form and function. Such building geometries can be obtained either from aerial photographs, laser scanning or digital topographic base maps. In our case we used topographic data from Swisstopo (1:25,000) and Ordnance Survey's (OS) MasterMap™ (1:1,250-10,000). After classifying every building we can create urban zones from them corresponding to the urban structure type (Figure 1). The application areas for these zones are manifold since they can serve as a basis for further geographic information analysis. The enriched data could be used in map generation with area tints for built-up areas as in the example of the German regional map. Another interesting application would be to use the zones within spatial web search engines to support the interpretation of spatial predicates like "near by" or "in" (Egenhofer 2002, Heinzle et al. 2003, Jones et al. 2002). For example the distinction between rural and non-rural area could be used to define the relation "*in* place name". We can further imagine using the data as a foundation for analysis in transport planning, socio-economic analysis and health care analysis. For instance Field and Beale (2004) apply diffusion patterns for diseases by Robinson (1998) to predict and estimate non-legal drug use. Such patterns could be further analysed and validated on a medium scale using information on urban structures. Our primary interest in classifying buildings into different types of urban structures, however, is driven by the need of adaptive map generalisation solutions for topographic map production (Weibel and Dutton 1999). In conventional map generalisation buildings and roads are generalised differently for different urban structures as described in SSC (2005). For instance buildings in inner city areas are usually aggregated to city blocks while in suburban areas alignments of single houses along roads are emphasised. Thus, to enable automated and adaptive generalisation solutions topographic data need to be automatically enriched with such urban structure information.
A short review of research on the recognition of urban structures is presented in Section 2. We outline our research objectives of this paper in Section 3. In accordance with these objectives we specify the urban

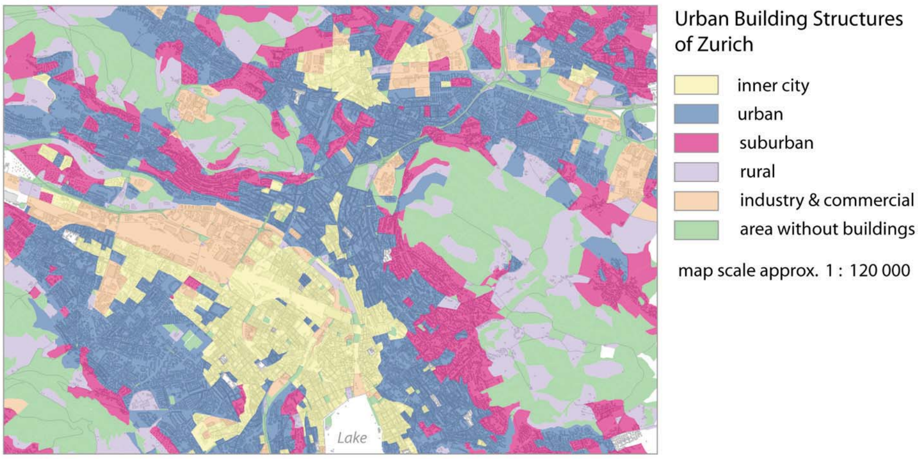


Figure 1. Urban structures of Zurich classified with the presented approach. Base Data: VECTOR25, reproduced by permission of Swisstopo (BA071035).

structures of interest and develop the classification approach (Section 4). In Sections 5 and 6 the recognition approach is evaluated with respect to its sensitivity to several parameters.

2. Research in Urban Structure Recognition

Recognition and analysis of urban structures is a research objective of several domains in geography. Our research attempts to address issues within the domains of urban modelling (Batty 1989) and cartography (Dent 1999). While urban modelling focuses on the theory of urban form, function and evolution cartography rather considers visual aspects of urban form and function for map making. The objective of urban modelling is to understand the development of urban structures including the understanding of physical and socio-economic distributions for purposes of socio-economic analysis and urban planning (Longley and Mesev 2000). The cartographic objective is the optimal presentation of urban form (structures) and function with respect to the map purpose, for instance education, planning or navigation; as well as map readability.

Marshall (2005) defines terms of urban morphology (e.g. urban pattern, urban fabric, urban form), the objects of classification and gives a comprehensive overview of typologies of urban patterns proposed in geography and especially urban morphology. Although research in urban modelling has a history longer than a century, research on algorithms and measures for (automated) pattern recognition to extract urban structures is fairly recent. This is probably due to the lack of large satellite image libraries and digital geographic datasets. Only advances in GIS, Surveying, Remote Sensing and Photogrammetry in the last decade made it possible that national mapping, space, postal or environmental agencies and other data providers could build up topographic databases with high resolution images and data.

Research in urban morphology on the identification and characterisation of urban patterns is in most cases based on remotely sensed data (Barnsley and Barr 1996, Donney et al. 2001, Herold et al. 2003). Here, the objective is to map land use and analyse the composition of land use and land cover with spatial metrics (Herold et al. 2005, Gustafson 1998). Currently new high-resolution satellites and the increasing number of topographic data products from mapping agencies (e.g. the OS ADDRESS-POINT™ and MasterMap™ products) offer new opportunities to combine satellite imagery with point based digital data (Longley and Mesev 2000, Mesev 2005) or carry out urban analysis with topographic data alone (Barr et al. 2004). These data sources allow performing pattern analysis with higher granularity and help to verify and improve models of socioeconomic processes. For example, Barr et al. (2004) could show the existence of a mapping between form (land cover) and function (land use) for built-up areas of two cities in the UK. They performed a structural analysis with a graph based approach on building data from the OS Land-Line product.

In contrast to urban modelling, the analysis of urban structures for map generalisation in cartography has been carried out directly on topographic datasets in the last years. On a small and medium scale, Boffet (2000) uses a polygon buffering approach on building geometries to identify different types of settlements such as towns, villages or hamlets for map generalisation purposes. An application of her work has been presented by Gaffuri and Trévisan (2004), showing how building blocks that are part of such settlements are generalised differently to preserve the urban structure in the maps. Edwardes and Regnauld (2000) try to identify homogenous density regions of cities (districts) for an adaptive generalisation of the urban road network. Heinzle et al. (2006) introduce graph based approaches for the extraction of road network patterns within and between towns. On a medium and large scale building alignments and building clusters have been extracted using geometric data structures including the Delaunay triangulation, the line Voronoi diagram, the Minimum Spanning Tree (Regnauld 2001) and other graph structures (Anders 2003). With respect to the previous research our work can be positioned between cartography and urban modelling since we aim to provide on the one hand semantically enriched base data for automated map production and on the other hand base data for further analysis in urban modelling and planning.

3. Objective and Research Questions

In the manner of Barr et al. (2004) we will classify urban land use structures. Barr et al (2004) aimed to show that a mapping between form and function can be established. We seek to extend their objective aiming to detect specific urban land use structures. Barr et al. (2004) characterise built-up areas by two morphological properties, area and compactness, and additionally proximity relations, where the latter are obtained from a Gabriel Graph. We use morphological properties and proximity relations as well but with three important differences. First, we use an extended set of morphological properties; second, we use vector based instead of raster based measures; and third, we establish proximity relations by buffering operations instead of using a graph structure. Since the buffering operations will result in attribute values for every building (i.e. properties) similarly to the morphological properties we can apply pattern classification approaches in feature space. Such a feature space is constructed by the building properties, whereas the position of a building in the feature space is defined by its property values. Thus, buildings with similar properties will be close to each other in feature space and may even form clusters. Note, that for the remainder of the paper we will use the term "*measures*" used in the map generalization literature in contrast to the term "*features*" used in classification and machine learning.

Considering that we aim to use classification approaches and an extended set of morphological and density measures, we can formulate the following research questions:

- What kind of urban land use structures are of interest in map generalization?
- Which variables and measures can be used to describe the urban structures sufficiently for our purposes?
- Which classification algorithms show good performance?
- What is the contribution of individual measures to the classification, i.e. which measures are discriminative?
- Which urban structure classes are difficult to detect or to separate?
- How different are land use patterns for different regions?

The next section will address the first two questions, and describe the basic approach to classify the building dataset. The remaining four research questions are subject to the discussion of the experimental results.

4. Defining Urban Structures, Measures and the Classification Methodology

4.1 Defining Urban Land-use Structures and a Set of Measures

The first task for our research is to identify the urban structures of interest. This definition should take the potential target applications into account. In our case we want to use the urban land use structures for the automated production of medium scale maps. Therefore we did a visual analysis of different topographic map series focusing on differences in visualisation and map generalisation of urban structures. The result of the visual analysis is shown in Table 1. Based on this analysis but also with respect to the usefulness for other GI analysis purposes we decided to specify five types of urban structures: (1) industrial and commercial areas, (2) inner city, (3) urban area (dense buildings), (4) suburban area (dispersed buildings) and (5) rural area (single buildings). Having defined the urban structures of interest we need to formalise them by their geometrical properties to discriminate the structures in a computer based approach.

In analysing these five types we see that their semantics is derived from two different perspectives. The structure type industrial and commercial area is defined only by its function, the other four types by their socio-economic function and form factors. Our available base data to carry out the structure recognition is solely the geometry of the buildings, as represented in vector map data. Thus, we can not include information on the function of a building into our approach and the classification has to be based solely on urban morphological properties.

This points us to the question whether it may be possible at all to detect our defined structure types using only morphological measures. Consider the experiment of selecting some arbitrary person from the street, to show her a map containing buildings and streets; and to ask her to draw the urban areas and point out the city centre. Even if the person is unfamiliar with the region shown on the map it is very likely that the person can outline the urban area and probably pick the true city centre after mentally combining own experiences with the perceived pattern structure of the buildings and the road network. From preliminary results of a similar experiment reported by Thomson and Béra (2007) but also from the results of Barr et al. (2004) we assume that a sensible classification can be realised by solely relying on rules of perception and consequently of Gestalt theory. In particular, Wertheimer (1923) developed a list of *laws of organisation in perceptual form*. These laws describe perceptual conditions which are necessary to let a human perceive groups of objects, hence describe properties of structures. Wertheimer (1923) identified several of these laws. The law of proximity and the law of similarity are the ones that we can obviously apply to define the structure types.

Country	Map	Urban Building Structures	
		Different Visualisation (different colours)	Different Map Generalisation of Buildings
France	Topographic Map – Série Verte 1:100,000	coloured areas for urban areas (towns) and industrial zones	amalgamation and typification of buildings in dense building areas; single buildings in other areas
Germany	Hessian Topographic Regional Map 1:100,000	coloured areas for dense building areas, low density building areas, industrial and business districts, single buildings in rural area	necessary for visualisation
Germany	Saxonian Topographic Regional Map 1:200,000		amalgamation in dense building areas, single buildings in other areas
UK	OS Landranger Map 1:50,000		amalgamation of buildings in urban areas; single buildings in rural areas
Switzerland (SSC 2005)	Topographic Map 1:50,000		introduction of generalisation zones for different settlement structures (e.g. hamlets, nucleated village, inner city, etc.)
Switzer-land	Cantonal School Map 1:100,000	coloured areas for inner city, industrial zone, dense building areas, lose building areas, single buildings in rural area	necessary for visualisation

Table 1. Visualisation of urban structures in different topographic maps.

The first law, proximity, describes that distances among individual objects of a group will be smaller than to objects that are not part of that group. Stated differently, this law proposes density or distance measures to identify urban structures. The second law suggests similarity among the group individuals. The notion of similarity we consider takes four visual variables (or aspects) into account: colour (object category), size, shape and orientation. The visual variable colour or category, respectively, is not useful in our case since we do not have functional information about the buildings. But we can use the other three visual variables. Based on these principles we selected five properties to describe our urban structures in a visual analysis. The five properties are built-up area density, building size, building shape (complex or compact), squareness of building walls, and finally building orientation. Thereby we define the orientation of a building by its major axis of the minimum bounding rectangle and restrict the range to values between 0 to 90 degrees (Duchêne et al. 2003). The definition of orientation is of course not suitable for round buildings but may suffice for this initial analysis, as round buildings are extremely rare, at least in western countries. For the visual analysis a topographic map of the City of Zurich in Switzerland has been used. The analysis result, given in Table 2, indicates that we should use all of the above properties, apart from orientation. Orientation does not discriminate between the structure classes, since it can not be expected that buildings of a particular structure type are aligned into the same direction. For instance all industrial buildings in several parts of a town will not be aligned to north.
In the next step we constructed measures to evaluate the structural properties given above. The size of a building is relatively easy to describe by calculating the building base area. Experiments have shown that a strong correlation exists between building size and the number of building corners (c.f. Burghardt and Steiniger 2005). Hence, we also use this measure to describe building size and shape. For the other properties we used (well-known) measures from the literature or derived our own, Table 3 summarises the measure set taken into consideration. The building shape is described by two indices from the literature: Schumm's shape index (MacEachren 1985) and building elongation (Bard 2004). Built-up area density is described by three buffer based measures. They evaluate area-related ratios either in terms of the number of the surrounding buildings or the built-up area within a predefined distance to the current building (see Table 3). As noted previously, the buffer measures should replace the description of object relationships by distance based graph structures that were used by Barr et al. (2004). This has the advantage that one obtains for one buffer measure a different value for every building. Somewhat special is a measure called "Number of holes" which emerges from the vector representation of courtyards for

Property	Urban Structure Type				
	Industry / Commercial	Inner City	Urban	Suburban	Rural Area
Building size	very large	large	large & medium	medium & small	large to small
Built-up area density	dense	very dense	dense	Low density	Open
Building Shape	complex & compact	compact	complex & compact	compact	complex & compact
Building Squareness	squared & not squared	not squared	squared	squared	Squared
Orientation	diverse main directions	No particular	No particular	No particular	Not at all

Table 2. Analysis of urban structures in a topographic map of Zurich (1:25,000) with respect to perceptual properties.

inner city or industrial buildings. Adopting these measures implies assumptions on the representation of buildings, especially with respect to the measures building squareness (BSq) and number of building corners (BCo). For instance we have to assume that collinear points on a wall segment are removed and round parts are digitised with the same vertex distance, not using, for instance, curve representations such as splines. This assumption is valid if we consider that the data providers, map agencies in our case, usually use a representation that does not require specific software features to read the data (as needed for spline representations) and that also presents a trade-off between necessary geographic detail and storage requirements. Furthermore, since we expect that data from the same data provider are of similar quality throughout the dataset, we also expect that our results will not be affected by issues of heterogeneous building representation within a particular dataset. Finally a set of three relational and six morphological measures has been established and implemented in the OpenSource GIS *JUMP* (Vivid Solutions, 2006). The geometry library *Java Topology Suite* (JTS) underlying *JUMP* delivers the algorithms for the calculation of polygon area and the number of holes as well as functions to evaluate topological predicates for the calculation of relational measures.

4.2 Initial Analysis of Separability and Selection of Classification Method

After having defined the set of measures we do not know yet whether the measures are sufficient to separate the five urban structure types. The problem of separability can be addressed by analysis of class-wise box-and-whisker plots for the measures, containing median value, upper and lower quartiles and outliers. Figure 2 shows these plots for four measures. This visualisation method indicates whether classes are separable by a simple one-dimensional *decision stump*, i.e. a decision threshold (cf. AdaBoost in Table 4). Note that this is a rather restrictive criterion for testing class separability. In particular, correlations among the different measures are not taken into account although one may easily envision situations where only the combination of features (e.g. the product of two measure values) is capable of discriminating between object classes. In Figure 2 it can be seen that the density measures separate quite well between the structure types. Thus, we can conclude that even a simple linear separation of urban structure types based on 1D stumps is possible.

With respect to the classification method used, only supervised classification makes sense in our case. Only supervised methods allow to make use of our pre-existing knowledge about the five target classes. Supervised classification approaches require the user to provide a set of training data with labels for every class (Duda et al. 2000). The algorithms learn from these given training objects (typically parameters such as weight vectors are determined during the training phase). The result of the training phase is a prediction routine that can be applied to new objects. Hence, the prediction routine or *classifier* partitions the whole feature space into different classes. Often, e.g. in discriminant analysis used in this paper, the

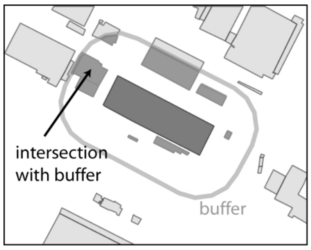
Morphologic Measures	Description	Relational Measures	Description
Building Area (BAr)	Polygon area minus the area of holes. JTS - Algorithm (VividSolutions 2006)	*No. of Buildings intersected by Buffer (NoBdg)*	Buffering of building and count of all buildings intersected by the buffer.
Number of Building Corners (BCo)	Count of polygon points of the exterior ring.	*Building Area to Convex Hull Area (BAHull)*	1) Buffering of buildings and selection of all buildings intersected by the buffer. 2) Calculation of convex hull around these buildings. 3) Calculation of area of buildings to area of convex hull ratio.
Building Shape (BSh)	Schumm's longest axis to area ratio (MacEachren 1985). $\frac{\sqrt{area/\pi}}{0.5 \cdot Longest\_Axis}$		
Building Squareness (BSq)	Mean deviation of all building corners from a perpendicular angle. (Bader 1999)	*Building Area to Buffer Area (BABuff)*	1) Buffering of buildings and selection of all buildings intersected by buffer. 2) Calculation of intersection regions (Buffer, Buildings). 3) Calculation of ratio area of intersection to area of buffer ratio.
Building Elongation (BEl)	Length to width ratio of the building's minimum bounding rectangle. (Bard 2004)		
Number of Courtyards (BCy)	Number of polygon holes.		

Table 3. Morphological and density indices to characterise the urban structures.

classifier is represented by a function that reflects the (decision) boundary between distinct classes. Decision boundaries divide the space in regions corresponding to the classes.

4.3 A Data Reduction Approach for Data Analysis and Method Evaluation

For the analysis of high-dimensional data, it may be useful to apply dimensionality reduction techniques that enable easy visual exploration. A visual exploration of the building data with respect to our objectives is useful for the analysis of class separability and the comparison of different building datasets (e.g. from different countries). Furthermore a reduction to 2-D also enables to compare the performance of a manual classification with the selected automated classification approaches. Clearly, reducing the dimensionality implies a loss of information. Therefore we have employed a data reduction technique which reduces the nine dimensional feature space (every measure represents one dimension, or feature) to two or three artificial dimensions, which aims to preserve as much relevant information as possible. Principle component analysis (PCA) is suitable for obtaining such a reduced feature space, because it exactly has the property to reduce the dimensionality of the data while minimising loss of information (Jackson 1991). We put forward a transformation from 9-D feature space into a 3-D and 2-D artificial feature space in three steps: First we exclude the measures *wall squareness* and *building elongation*, since both poorly discriminate (cf. the box-and-whisker plots) and building elongation largely correlates with the shape index measure (see Section 5.3). In the second step transformation parameters were obtained from PCA employing an initial sample set of about 2000 buildings to reduce the 7-D space to a 3-D artificial space. Here the target dimension has been chosen to be three dimensional for two reasons. The

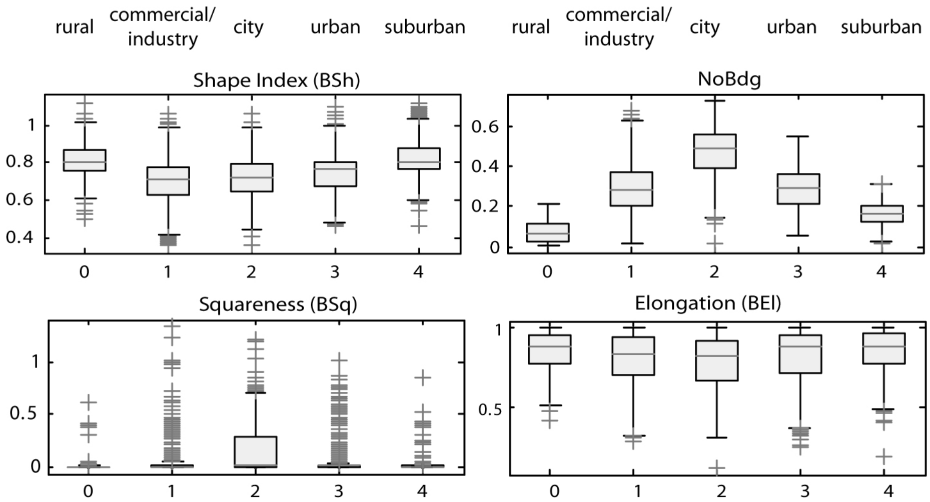


Figure 2. Box-and-whisker plots for four measures calculated from 2,000 buildings of the Zurich data set. Class separability of *squareness* is low but high for the buildings-in-buffer index (NoBdg).

first reason is that a human usually has no problem perceiving information from a 3-D space with appropriate visualisation tools. And the second reason is that the loss of information should be kept low. To evaluate a possible loss of information we applied the Kaiser, or *average root*, criterion (Jackson 1991, Hill and Lewicki 2006). This criterion states that one should retain the principal components with eigen-values larger than one for normalised data. Finally, in the third step, we employed a mapping that projected our data from the 3-D space, spanned by the first three principal components of a PCA of 7 variables, into an artificial 2-D space. This enables us to present the data in this paper and to compare the different datasets of our experiments. The results of the data transformation from 9D to 3D and to 2D are shown in Figure 3.

4.4 Classification Approach

Our approach to classify the buildings uses machine learning algorithms to detect the decision boundaries between the urban structure types. For our experiments we have implemented four different classification techniques: a *Batch Perceptron* algorithm, a *Minimum Squared Error* (MSE) algorithm based on pseudo inverse, AdaBoost with *decision stumps* (Schapire 1999) and a *Support Vector Machine* (SVM), where

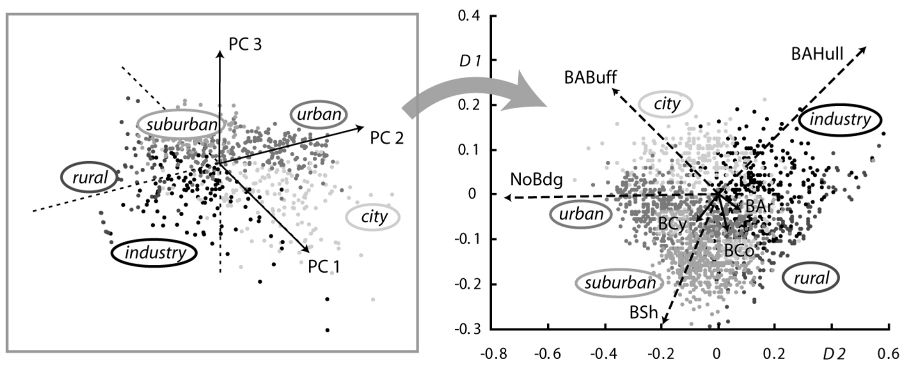


Figure 3. The sample data transformed from 7-D into a 3-D space (using a PCA) and further into an artificial 2-D feature space. The vectors in the right plot, which is similar to a Biplot (Gabriel 1971), indicate the direction in which positive changes of measure values act (e.g. large and small values). The vector length indicates the weight of the variable.

we have employed the *SVM^{light}* software package (Joachims 1999). This SVM implementation offers a number of alternative approaches by application of different transformation kernels of which we have used three. For a general introduction to these classification algorithms we refer to Duda et al. (2000). For the purpose of this paper we provide a short description of the approaches in Table 4. However, we would like to specifically emphasise two issues. The first is that all approaches do not require knowledge about the underlying probability distributions of the data (see Duda et al. 2000: 215), but clearly they make assumptions at least about the distribution of the given (building) measure values for each urban structure class. Second, the Batch Perceptron algorithm and the MSE algorithm yield linear decision boundaries, whereas AdaBoost and the SVM approach can calculate non-linear class separations. We hypothesise the latter type of algorithms to have higher classification accuracy. The implementation of the algorithms was done in *MATLAB* (MathWorks Inc.) and *SVM^{light}* has been connected to *MATLAB* using an interface provided by Tom Briggs (2005).

After having defined the measures and after having selected the classification algorithms we can now define the general approach to classify the buildings. Basically the procedure can be organised into the following steps (see Figure 4):

1. Characterise all buildings with the measures defined in Section (4.1) in *JUMP* GIS.
2. Store the measure values and transfer to *MATLAB*.
3. Load the training data set, labelled with the structure type, and standardise the data. Calculate the decision boundaries for every class pair with one of the algorithms described above. Since we have n=5 types we obtain $0.5*(n^2-n)=10$ decision boundaries.
4. Load the data which should be classified and standardise them with parameters from the training data. Classify every building with the 10 obtained decision boundaries, which results in 10 type assignments for every building.
5. Assign the final type by majority vote over the 10 assignments.

If reference data is available, then it is possible to evaluate the accuracy of the classification in a further step. The indices used to quantify the classification accuracy are explained below in Section 5.3.

4.5 Considering spatial autocorrelation

When classifying the buildings it is very likely that a building will have the same structure type as buildings in the neighbourhood owing to the underlying zoning structure. This effect of spatial autocorrelation can be considered as additional information which could improve the classification accuracy on a medium (generalised) map scale. Note that incorporating spatial autocorrelation makes only sense for a generalised map scale, since a large supermarket (commercial structure) situated in a residential area (urban or suburban structure) will obviously break the assumption of neighbourhood homogeneity. Here, the application of spatial autocorrelation will lead to a misclassification of the super market.

The classification algorithms described above can not deal with the additional information on neighbourhood homogeneity. Therefore we have implemented a spatial mode filter to enhance the classification results after the initial classification. The mode filtering is realized by a buffering of a building (e.g. 200m) and determination of the dominant class within the buffer. The obtained dominant class is subsequently assigned to the building. This mode filtering is similar to a focal majority operation

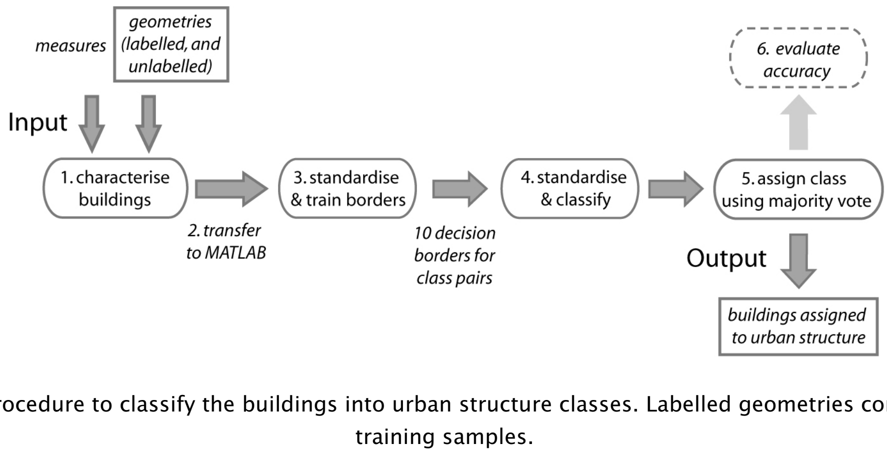


Figure 4. Procedure to classify the buildings into urban structure classes. Labelled geometries correspond to training samples.

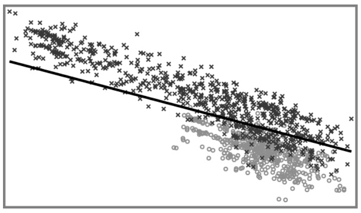
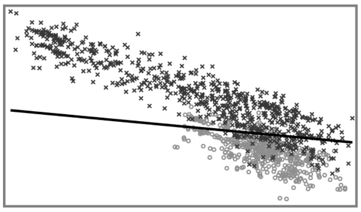
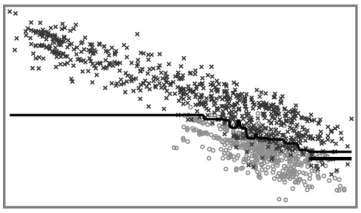
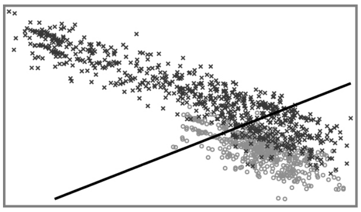
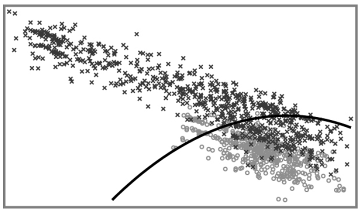
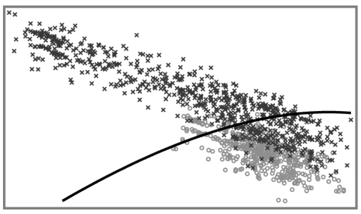
Classification Algorithm	Description	Notes on processing and parameters	Example: resulting decision boundary for two classes described by two features (2-D).
Batch Perceptron (BP) (Duda *et al.* 2000)	Class separation with a linear boundary which is iteratively displaced until the error is minimal. The iterative process is not converging for non-separable classes. Here, the boundary with smallest error is selected after all iterations.	3·n iterations, where n is the number of training samples; augmented feature vector	
Minimum Squared Error with Pseudo Inverse (MSE) (Duda *et al.* 2000)	One step calculation of the separating linear boundary from all samples by minimizing the squared length of the error vector. The calculation is sensitive to outliers. Large sample sets (>1,000) should be avoided since matrices may become very large.	augmented feature vector	
AdaBoost with decision stumps (Schapire, 1999)	Training with a set of so called weak learners (e.g. axis parallel boundaries), and final classification by weighting the single classifier results. Incorrectly classified samples obtain a higher weight for the training with the next learner. The learner itself obtains a weight according to its classification accuracy and with respect to all samples.	combination of 100 decision stumps, where a decision stump is an axis parallel decision threshold	
Support Vector Machine(SVM) (Cristiani and Shawe-Taylor, 2000) implementation: SVM^{light} by Joachims (1998)	Using different kernels the data are transformed into a higher dimensional space. Afterwards iterative estimation of the decision boundary by searching the maximum distance between the classes. The support vectors are the training samples closest to the boundary. x = samples, a = x(:,i), b = x(:,j)	termination criterion calculated by SVM^{light} : c =[avg (x·x)]$^{-1}$; biased hyperplane ($b=1$)	 Linear Kernel
	▪ Linear Kernel	---	
	▪ Radial Basis Function Kernel (RBF): $\exp(-\gamma\,\|\|a-b\|\|^2)$, $\gamma=1/(2\sigma^2)$	$\gamma = 0.3$	 Radial Basis Function Kernel
	▪ Polynomial Kernel (PK): $(a{\cdot}b + 1)^d$	$d = 2$	 Polynomial Kernel

Table 4. Used algorithms for discriminant analysis.

applied to raster data. Note that there are models, such as discriminative random fields (Kumar and Hebert 2003), that can be used to directly incorporate spatial homogeneity preferences. However, this induces additional computational costs and tractability problems during the inference. For these reasons, we have abstained from considering such an approach.

5. Data, Experiments and Results

5. 1 Data

For our tests we used building data provided by Swisstopo and the Ordnance Survey (OS), the Swiss and the British national mapping agency, respectively. The Swiss VECTOR25 data, containing building data from Zurich, are vector data digitised from the national topographic map of scale 1:25,000. The Ordnance Survey building dataset is extracted from the MasterMap^{TM} product which has a map scale of 1:1,250 for the area of Southampton. We defined for both datasets a training sample set and validation dataset, whereby the first set is used to train the decision boundaries and the second for the accuracy assessment. For Southampton the training data selection has been accomplished by an OS staff member. The classes have not been assigned to individual buildings. Rather we assigned the structure type to an entire area, which essentially results in an areal generalisation. With respect to our supermarket example above, we would have assigned the supermarket the label of the surrounding suburban houses.

From the VECTOR25 and MasterMap^{TM} product specification it is obvious that the corresponding map scales differ by a factor of 20. This may influence the classification accuracy in various ways and will lead to an inappropriate comparison between the two datasets. To make the datasets comparable and subsequently estimate the influence of map generalisation we generalised the Southampton buildings. In order to do so we used the Swiss map generalisation specifications described in *Topographic Maps – Map Graphic and Generalisation* (SSC 2005). With respect to building data the following generalisation rules have been applied to Swiss data:

- Maintain original position.
- Omit only unimportant buildings with area < 49 m^2.
- Simplify building edges that are shorter than 0.35 mm; otherwise leave unchanged.
- Emphasise characteristic basic shape.
- Typify if too many small buildings are omitted.

Note that the generalisation effects for buildings are still relatively small in transitions between large map scales down to 1:25,000. In consequence we generalised the Southampton data in a batch processing approach using the map generalisation operators: building aggregation, elimination, simplification and enlargement (McMaster and Shea 1992) to the target scale of 1:25,000. The generalisation algorithms used are partly described in AGENT (1999) and can be accessed by a Web Generalisation Service (Burghardt et al. 2005).

5.2 Accuracy Assessment

Before performing and evaluating the classification we need to define measures of classification accuracy and certainty. To evaluate the results we used on the one hand the total accuracy (i.e. the fraction of objects misclassified) and on the other hand Cohen's Kappa index (Lillesand et al. 2000). In contrast to the total accuracy the Kappa index takes the probability of incorrectly classified objects into account with values ranging from 0.0 (worst) to 1.0 (best). We are aware that the standard Kappa statistics has deficiencies when geo spatial phenomena including effects of spatial autocorrelation are assessed (Pontius 2000, Walker 2003). Nevertheless, we will use only the standard Kappa statistics as evaluation criterion for two reasons. First, the classification results of our experiments should be much more affected by the chosen measures and their parameters than by the selected algorithms. Second, none of the classification algorithms used does account for information on spatial autocorrelation per se, thus, they should perform in a similar way, apart from the fact that the shape of the decision boundaries differs between the algorithms.

The certainty of correct classification for a specific building can be assessed by evaluation of the distance between the object position in feature space and the decision boundary (see Figure 5). Therefore, based on the newly assigned class label (i.e. structure type), the distances to the decision boundaries of the four other classes are calculated and the smallest distance is taken as value of certainty. Structure type assignments with high certainty will have large distances. Values close to zero can be interpreted as objects which could be assigned to two classes. The left plot in Figure 5 shows the distribution of certainty values for a classification based on only two measures, made especially for illustration purposes.

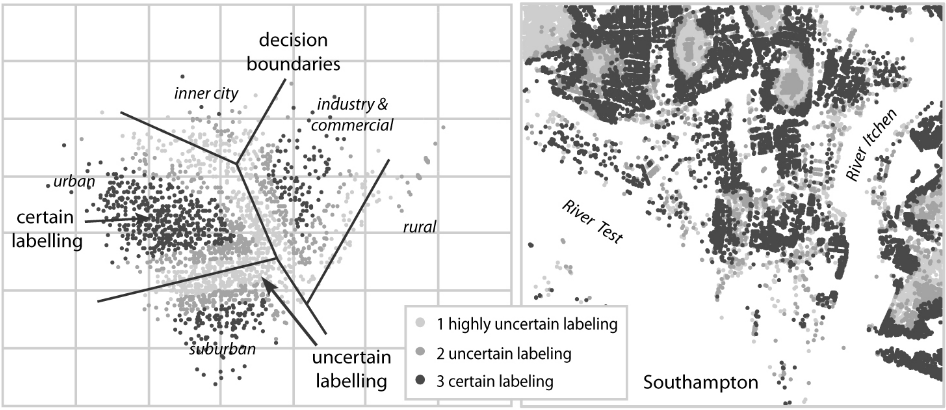


Figure 5. Certainty assessment of classified, individual buildings by evaluating the distances to the decision boundary. Left: Certainty of classified buildings in 2-D feature space for an artificial example. Right: Map of classification certainty for buildings from Southampton whereby every building is visualized as point with real-world coordinates. Lightness represents the certainty level in three groups: group 1 contains the first 1/7th of the buildings close to the boundary, group 2 the second 1/7th of all data and group 3 the remaining 5/7th of the data.

The right plot is a certainty image in real-world coordinates obtained for a 9-D SVM classification of the Southampton data. Note that it is not possible to compare the certainty values of the different classification algorithms, since the feature spaces do not have the same metric properties (particularly in the SVM approach).

5.3 Experiments and Results

A number of experiments have been performed to address the questions raised in Section 3 and to evaluate the classification approach. One classification result for Zurich training data is shown in Figure 6. In the following we present several experiments that have been performed in order to answer on the research questions:

Class Separability – In this experiment, we try to get an idea about whether the chosen approach generally returns useful results and whether the five classes are separable. The separability test can be done in two stages of the classification process: either by an assessment of the pair-wise classification accuracy after the training stage (step 3 in Figure 4), or by evaluation of the confusion matrix (Lillesand et al. 2000) during the accuracy evaluation (step 6). Sample results for separability evaluation by pair-wise classification are shown in Table 5. Two error estimates are given, the first denotes the percentage of incorrectly classified samples for both classes, and the second in brackets is the error for the class with the smaller sample set. The particular classification approach seems to be promising since only up to a fifth of the samples are classified incorrectly.

Class	Rural	Industry	Inner city	Urban	Suburban
Rural	---	0.11 (0.14)	0.04 (0.01)	0.05 (0.22)	0.06 (0.20)
Industry		---	0.17 (0.12)	0.09 (0.21)	0.05 (0.12)
Inner city			---	0.08 (0.21)	0.03 (0.08)
Urban				---	0.11 (0.12)
Suburban					---

Table 5. Error [0..1] for pair-wise classification to assess class separability. In brackets the error ratio is given for the class with the smaller sample set. High error rates are shaded in grey. Zurich data (25k), MSE Algorithm, all 9 measures, 50 m Buffer.

Classification Result for Zurich Training Samples 1:25 000

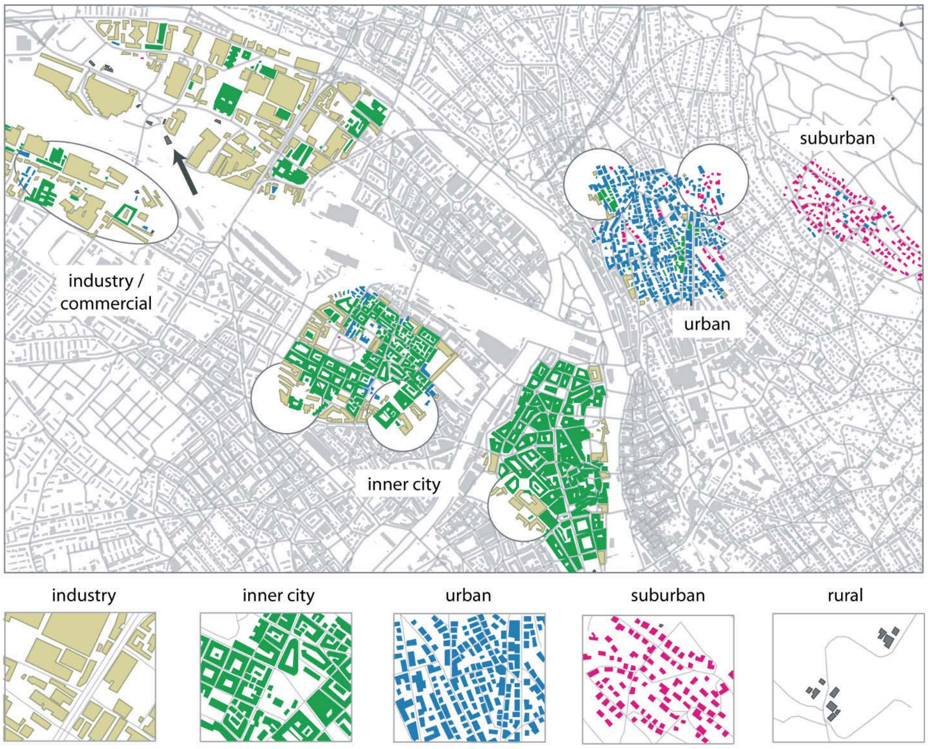


Figure 6. Classification results for the Zurich training data (display scale approx. 1: 41,000). Incorrectly classified buildings will have a different colour than the majority of buildings in the partition. Circles mark edge problems. The arrow indicates the case of a misclassified industrial building discussed in Section 6.1. Data: VECTOR25, reproduced by permission of Swisstopo (BA071035).

Assessment of Classification Algorithms – In the second experiment we evaluated whether the automated discriminant analysis approach achieves sufficient classification accuracy and how different classification algorithms perform. The results of the experiment, using the Kappa statistics as evaluation criterion, are given in the Table 6. The table shows classification results based on a full set of 9 measures (9-D), a set of 7 measures (7-D), and a classification based on the first three principal components of the PCA transform (3-D Scores). The average Kappa value is about 0.66 corresponding to a total accuracy of 75 %. In other words, a performance nearly 3.5 times better than a classification by chance has been reached. The values indicate a comparable performance of all discriminant analysis algorithms.

Impact of Regional Factors on Urban Structures – We compared the Zurich Data and the generalised Southampton data, both datasets prepared for a map scale of 1:25,000, in the 2-D presentation. Figure 7 shows that in 2-D the structure classes do more strongly overlap each other for Southampton. One can further see that the Southampton buildings are less clustered than the Zurich buildings. Using the measure indicators for the analysis, one can infer that the suburban and urban buildings of Southampton have more buildings per area but with larger free space between the buildings. This implies that average building size is smaller. To evaluate this difference quantitatively we classified the generalised Southampton buildings with decision boundaries obtained from the Zurich training data set. The Kappa value was approximately half of the value for the classification with the Zurich data and the total accuracy decreased to 60 percent (see Figure 8). In a second classification, carried out with the original Southampton buildings (1:1,250), it appeared that the structure type *inner city area* and *industrial area* are harder to detect with the measures used, compared to the Zurich data. In consequence the Kappa index decreased by 0.06 units to 0.6 (see Figure 8). Surprisingly, the total accuracy was similar (0.74), which may be due to a higher fraction of buildings from well separable types such as *urban* and *suburban* area.

Influence of the Buffer Size – In the previous experiments the buffer radius of the density measures was set to 50 m. Varying this parameter should have an influence on the classification result, which can be concluded from the work of Le Gléau et al. (1997) and Boffet (2001). Le Gléau et al. (1997) analysed the definition of towns and built-up zones in Europe to evaluate how comparable socio-economic statistics

Dimension	Discriminant Analysis Algorithm					
	Batch Percpetron	MSE	AdaBoost	Support Vector Machine (SVM)		
				linear	RBF	PK
3 scores (PCA from 7-D)	0.57	0.58	0.57	0.57	0.58	0.58
7-D	0.67	0.66	0.66	0.67	0.66	0.68
9-D	0.67	0.66	0.66	0.67	0.66	0.67

Table 6. Kappa classification accuracy for different algorithms and different dimensions (i.e. sets of measures). Zurich data (25k), buffer size set to 50 m.

are, which are based on statistical area units. They report that statistical area units are not only defined administratively or population based but also with respect to continuous built-up zones. They describe continuity by the maximum distance between buildings. These maximum distances are adapted to the regional urban structures and are historically founded. Maximum distance values given by Le Gléau et al. (1997) vary between 50 m (e.g. Scotland) and 200 m (e.g. France). Research by Boffet (2001) dealt with the extraction of settlement types using a building buffering approach. She also analysed the influence of the buffer radius to optimise the settlement identification for French data and for mapping purposes. She concluded that a buffer radius of 25 m was best for her purposes.
Based on these results from the literature we conducted a number of tests to analyse the influence of the buffer size on the structure type classification. We chose radii of 25 m, 50 m, 100 m, 200 m and 500 m and analysed the effect on classification accuracy, certainty of type assignment and computation time required for the building characterisation. The results shown in Table 7 indicate that a maximum of classification accuracy and certainty is reached for a 200 m buffer radius. Here, the classification accuracy increased by 11 % changing from 50 m to a 200 m radius. A contrary but predictable behaviour can be seen for the computation time which is about four times larger for a 200 m radius than for the 50 m buffer. The influence of buffer size has not only an effect on the classification but also on the spatial mode filter. The results of spatial mode filtering are discussed below.
Contribution of Measures – As a consequence of the previous experiment the question emerges what the contributions of the different measures are to the classification result. This question is not easy to answer since on the one hand the contributions depend on the class separation property of each measure and on the other hand they depend on correlations between the measures. Both issues again are influenced by the chosen data set and further by map generalisation effects. The issues of correlation and generalisation are addressed below separately. The following evaluation of the contribution of measures is based on the classification accuracies shown in Table 8.

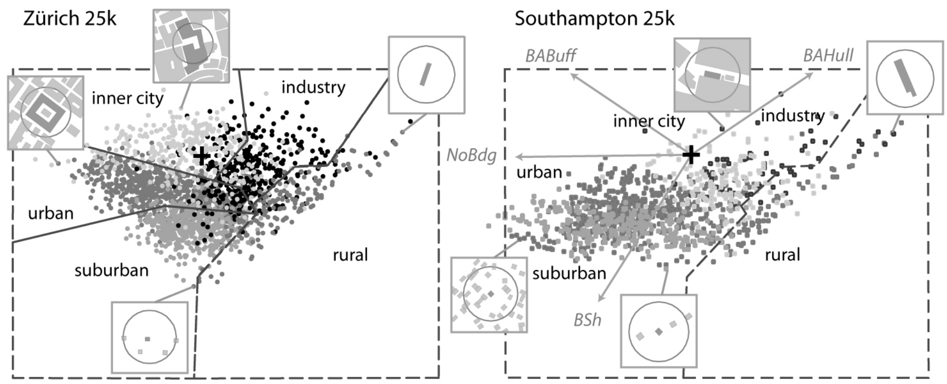


Figure 7. The Zurich buildings (ca. 2,000) and generalized Southampton buildings (ca. 1,000) in artificial 2-D feature space. Sample data of the same structure type have different positions for both cities. The types of Southampton overlap to a greater extent, which may explain inferior classification results.

Figure 8. Classification results for three different data sets. Classification approach: SVM with RBF, all 9 measures, buffer size was set to 50 m.

In Section 4.2 we argued that we can exclude the measures *Wall Squareness* and *Building Elongation* in a first step to obtain a 7-D presentation. In Table 8 the value of the Kappa index for all measures (*9-D*) and without *Wall Squareness* and *Building Elongation* (*7-D*) differs at most by 0.01 units for the Zurich data. Thus, one can infer that both measures make only a very small contribution to the classification. But it should not be concluded that the measures can be generally discarded, since the *Elongation* measure shows a better class separability for the Southampton data (1:1250) than for the Zurich data. We also tested classifications based on the first three components resulting from the PCA (named *3-D scores*) and on the projected scores (*2-D*). Both tests are useful to evaluate the loss of information during the data transformation and hence the expressiveness of the 3-D and 2-D visualisation such as Figures 3 and 7. In the "3-D scores" classification the Kappa values for both datasets decreased by 0.08 units corresponding to a 70 % reduction of variance (value obtained from the PCA). However, returning to the influence of specific measures, we tested a classification without the three density measures (*6-D without buffer measures*) and one with the density measures only (*3-D with buffer measures*). From the table it is apparent that the classification based solely on the density indices reaches nearly the original classification result. In detail the density measures cover about 99 % of original Kappa for Zurich and 91 % for Southampton. And as further experiments have shown, these values do increase for a 200 m buffer radius. In contrast a classification without the density characterisation drops the accuracy for Zurich down to 23 % and for Southampton down to 36 % of the original Kappa value. These results can be explained largely by the good separability properties of the density indices, exemplified in Figure 2 (top-right plot) for the *Number of Buildings in Buffer* measure. Note particularly the different classification results for 6-D between Zurich and Southampton (Table 8), which may be explained by regional factors and hence by the separation property of the *Elongation* measure.

In the literature on geographic pattern analysis the *Nearest Neighbour Index* (R-Index) is often emphasised, which measures the spatial distribution of points (Mesev 2005, Haggett 2001). We added the R-Index to the measure set (*10-D*) to carry out an additional classification experiment. The building centroids were used as points. According to the result presented in Table 8 the influence of the additional index is very subtle. The classification accuracy for the Zurich data rose by 0.7 % but decreased by 0.1 % for Southampton. The relation of the R-Index to the density measures will also be addressed in the

	Buffer Size				
	25 m	50 m	100 m	200 m	500 m
Accuracy [0..1]	0.74	0.84	0.92	0.95	0.95
Kappa [0..1]	0.66	0.78	0.90	0.94	0.93
Certainty [0..1]	0.79	0.92	1.0	1.0	1.0
Time [sec]	20	30	50	140	740

Table 7. Classification results for different buffer sizes. Data: Zurich (25k) – classification of training data only. Classification approach: SVM with RBF, all 9 measures.

Dataset	Dimensions						
	2-D (projected scores)	3-D scores (PCA from 7-D)	3-D (with buffer measures)	6-D (without buffer measures)	7-D	9-D	10-D (9-D with R-Index)
Southampton 1:1,250	0.37	0.51	0.55	0.22	0.59	0.60	0.60
Zürich 1:25,00	0.44	0.58	0.65	0.15	0.66	0.66	0.67

Table 8. Kappa classification accuracy when different sets of measures are used. Classification approach: SVM with RBF, 50 m Buffer.

following paragraph to explain its minor influence on the classification results.

(Cor-) Relations between Measures – To analyse the relations between the measures we used three methods: the calculation of correlation coefficients, PCA and Factor Analysis (FA). Similar to Riitters et al. (1995) we first evaluated the correlation coefficients and afterwards the composition of the factors. PCA is used to estimate the initial number of measure groups (factors), based on the average root criterion (Jackson 1991). The number of factors is required to perform the "orthomax" FA in MATLAB. Below we present the result of the correlation analysis first and afterwards the results of the FA.

Unlike Riitters et al. (1995) in their evaluation of structure metrics for landscape analysis, we did not find correlation values of 0.9 or larger to exclude some of the participating measures from our initial set. The maximum correlation values reached 0.6 to 0.8 for the measures *number of building corners* and *building area* (results not presented in tables). The second largest correlation value of 0.5 to 0.6 exists between *building elongation* and *shape index*. Problematic for the evaluation of the correlation are large variations of the correlation values, especially for the buffer indices. The variation of correlation values is caused by the heterogeneity of the selected buildings, the regional differences of urban structures, the buffer radius, and by map generalisation effects. For the two mentioned combinations of measures stable values appear in all situations. Other combinations of measures do also reach high correlations but show strong variations. For instance *NoBdg* and *BAHull* have the lowest correlation of 0.20 for Zurich validation data (50 m buffer) and highest value of 0.82 for the Southampton training data (200 m buffer).

The *R- Index*, which has only little effect on the classification result, shows also large variations in the correlation values with the other buffer indices. For every analysed dataset the index reached a correlation value of at least 0.4 with one buffer measure. Here the emphasis is on "one" since the index does not correlate with a particular density index, rather it correlates in an alternating way with one of the density measures, depending on the dataset.

Finally, according to the criterion of an appropriate high correlation coefficient near 0.9 given by Riitters et al. (1995) we did not exclude indices from our measure set.

After the assessment of correlation coefficients we performed a FA. In the first step we conducted a PCA to estimate the number of factors. The analysis of the resulting components yielded that four components exist with an eigen-value larger than 1.0. Hence, the set of 10 measures may be assigned to 4 groups. To stay more flexible we introduced as hypothesis five groups (i.e. factors) in the orthomax FA. The results of the FA were again different for the different data sets. Table 9 presents the factor loadings for the Zurich training data. Ordering the factors by the explained variance (left to right) and analysing their composition, the first factor of all data sets can be described as size factor. This factor is based on the measures *building area*, *number of building corners, number of courtyards* and usually to a lower fraction *building squareness*. It is not surprising that this factor explains most of the variance, since *building area* is the most strongly varying index. The importance of the four remaining factors changes across datasets. One of the factors can be described as shape factor, combining *building shape* and *building elongation*, and has either the second or third rank depending on the test dataset (in Table 9 the third factor). The meaning of the other factors changes, like their rank, and usually groups two density measures in different combinations. In general one could characterise the remaining factors as describing building structure and building density.

Measure	Factor Loadings [0..1]				
	1. Factor	2. Factor	3. Factor	4. Factor	5. Factor
Area	**0.64**	0.04	-0.16	0.07	0.18
Shape	-0.16	-0.02	**0.98**	-0.02	0.04
Elongation	-0.06	-0.04	**0.53**	-0.04	-0.02
Squareness	**0.46**	0.06	-0.05	0.02	0.01
Corners	**0.99**	-0.04	-0.10	-0.01	-0.01
NoBdg	-0.01	**0.77**	-0.00	0.06	**-0.42**
BAHull	0.15	-0.06	0.00	-0.22	**0.78**
BABuff	0.24	**0.82**	-0.12	**0.35**	**0.36**
Number of Courtyards	**0.50**	0.04	-0.02	0.00	0.05
R-Index	0.05	0.23	-0.08	**0.93**	-0.27
explained variance (%) from PCA	26.6	19.8	13.5	10.3	8.4

Table 9. Factor loadings obtained by an orthomax Factor Analysis on the Zurich validation data characterised with a 50 m buffer. The factor loadings indicate correlations and possible groupings of measures. High values are in bold.

Influence of Map Generalisation – Effects of map generalisation can be analysed between the original Southampton data from OS MasterMap^{TM} and the generalised Southampton data for scale 1:25'000. In particular the evaluation showed that correlations between measures do change. For example the correlation between *building area* and *number of corners* increases. Decreasing correlation was found between *NoBdg* and *BAHull*. Yet a case of a reversing correlation, from positive to negative, appeared between *R-Index* and *BAHull*. These effects - in particular the increasing correlation among shape and size indices - may be explained by the map generalisation operations used. This has also been pointed out by Burghardt and Steiniger (2005).

Results of Spatial Mode Filtering – Following the assignment of the structure type labels to the individual buildings we applied a spatial mode filter. The questions emerging from that procedure are: "Which buffer radius should be chosen?", and "How often should the filter be applied to a) achieve spatial autocorrelation and b) to gain a similar generalisation effect introduced by the sample selection procedure?". In our opinion it is difficult to address the parts a) and b) separately. Therefore we evaluated only how fast a maximum classification accuracy with respect to the validation data was reached. We like to emphasise that the criterion of maximum accuracy may not be the best choice. Too many filter runs, resulting in a maximum accuracy, can lead to a too strong degree of smoothing which is inappropriate to the later application purpose, e.g. map production or urban socio-economic analysis.

The results of the experiment listed in the Table 10 show that the number of filter runs depends on the buffer radius chosen. Usage of a 50 m buffer mode filter requires more runs until a limit of improvement is reached. The 200 m buffer mode filter shows best performance by improving the classification accuracy between 5 (dataset B) and 20 % (dataset A), even after a single run. The table also shows evidence that improvements can still be reached if the dataset has been characterised with density indices based on a 200 m buffer radius.

Setting	Original Kappa	Number of Filter Runs			
		1x	2x	3x	4x
Dataset A 50 m Filter Buffer	0.68	0.81	0.84	0.85	0.86
Dataset A 200 m Filter Buffer	0.68	0.91	0.91	---	---
Dataset B 50 m Filter Buffer	0.94	0.97	0.97	---	---
Dataset B 200 m Filter Buffer	0.94	1.0	---	---	---

Table 10. Classification improvement by multiple application of a spatial mode filter.

6. Discussion

In Section 4 we gave some answers to our first two research questions formulated in Section 3 with respect to the definition of the urban structures and the set-up of basic measures to characterise urban structures. Further we developed the classification approach based on discriminant analysis techniques. Before we will address the remaining four research questions, we start off the discussion with some general notes on the classification process.

6.1. Notes on Processing and Evaluation

Some uncertainties in the evaluation caused by the test configuration have to be mentioned. The spatial mode filter results in an areal generalisation effect. Since training data have been selected by assigning all buildings contained in an area to a particular target class the selection process itself does also have a certain generalisation effect. Recalling the supermarket example above, this leads to the situation that a supermarket in a residential area is classified in the training data set incorrectly as suburban building. The classification will probably assign the supermarket to the correct type (i.e. commercial) if the influence of the size indices is large enough. Now, the subsequently applied mode filter does reclassify the correctly classified supermarket from commercial to suburban again. Hence the approach classified the supermarket incorrectly on the one hand but on the other adapts the class assigned to the supermarket to the training data, which in turn results in an improvement of the classification accuracy. The same effect - not for a supermarket - can be seen in Figure 6 (black arrow), where houses in an industrial area of Zurich are classified as rural.

A further side effect is caused by buildings located on the edge of test areas, resulting in an increasing incorrect classification (Figure 6, see circles). Due to edge effects the density measures are incorrectly calculated, especially for larger buffer sizes. This effect can be minimised if large, compact and contiguous sample sites are chosen.

The third issue addresses the generalisation property, here meant in terms of machine learning, of the discriminant analysis algorithms listed in Table 4. Unfortunately we can not rule out that the current algorithm parameter settings lead to an overfitting to the training data. Here, over-fitting means that the discriminating boundary adapts too much to single training examples, which would be considered as outliers in a manual classification. However, since we used an independent validation dataset for accuracy assessment such effects should be compensated in the error calculation.

6.2 Addressing the Remaining Research Questions

Evaluating the Measures – To answer the question about the contribution of the measures to the classification includes revisiting the answer to the first question concerning the appropriateness of the basic measure set. From the results of the experiments we have seen that it is possible to evaluate the contributions and measure relations for a specific dataset. However, it has also been shown that these results can have large variations with respect to the influence of regional – country specific – factors, the buffer size chosen for the density measures and further the effects of map generalisation and hence, map scale. From the correlation analysis, which yields low to medium correlation, we can conclude that all measures describe individual properties of the building data. However, the results from the Factor Analysis indicate that we can group the measures into five distinct factors. Moreover, the classification experiment based on the three buffer-based (i.e. density) measures reveals that one can reach high classification accuracy without using morphological indices. Our tests indicate that we should possibly carry out further experiments based on a set of five measures, consisting of the three buffer based density indices, the shape index and the *number of building corners*. We recommend using the latter measure and not *building area* because it has on average the highest factor loadings for the size component.

The large variation of correlation values and the different classification accuracy for the Zurich and Southampton data points to one further implication. The current measure set may not be the best for urban structures of Southampton. This is suggested by a higher degree of incorrectly classified objects for Southampton compared to Zurich. Therefore further measures could be analysed whether they better describe these building patterns. These measures should address two issues. The first issue concerns the urban fabric of Southampton, which contains more buildings per area unit but with larger spacing between the buildings (i.e. on average the buildings are smaller). The second issue emerges from the evaluation of the generalisation experiment and implies the recommendation to adapt the measure set to the data resolution. In our specific case the MasterMap^{TM} data have a higher spatial resolution compared to the VECTOR25 data resulting in more detailed building geometries. This recommendation is additionally supported by the observation of increasing correlation between measures for lower spatial resolution.

A final remark is warranted with respect to the results of Barr et al. (2004). Much to their surprise they discovered a low influence of proximity measures on class separability. In our experiments we could show the opposite effect of dominating proximity/buffer indices. We believe that this is an effect of scale and the structure types that have been defined for the classification.

Classification Algorithms – The fifth research question has addressed the performance of different classification algorithms. The expectation was that the classification with non-linear decision boundaries will be better than with linear ones. The results of Table 6 for Zurich show that none of the algorithms seems to perform significantly better than the others. Although in further tests with 9-D and 3-D data we observed on average best results for the Support Vector Machine with a quadratic polynomial kernel. However, our classification study also indicates that it is difficult to extrapolate this finding to other data sets of different geographical regions, with different pre-processing, or even different sets of measures. Considering the effect of the number of measures, more features can result in more poor minima for iterative algorithms or overfitting in the case of small sample sets. Put differently, more training samples are needed if more measures should be used.

Separability of structure types – The question which should be answered now concerns the identification of urban structure classes which are difficult to separate from each other or difficult to detect. From tests of pair-wise class separability, as given in Table 5, we observed a general problem in distinguishing inner city from industry and commercial areas. Both classes do also overlap with the urban area class. Sometimes the definition of a boundary between rural and suburban area is difficult. A similar problem of a fuzzy boundary exists between urban and suburban area. The reason in both cases is the underlying spatially smooth transition process from one urban structure class to another class. With respect to map scale we could observe a worsening of the separability for all class pairs involving inner-city objects with stronger building generalisation. This does not hold for combinations with rural classes since buildings of the rural class are mainly defined by their neighbourhood properties, not building shape.

Influence of regional factors - The final question we need to address is the following: Are built-up area patterns from different regions or countries similar to such a degree that we need only one initial definition of prototype buildings for every urban structure? The answer should be given with respect to Figure 7. One can see that buildings, representing the same urban structure type, are differently located in the artificial 2-D feature space for Zurich and Southampton. Additionally the classes are harder to separate in the Southampton dataset. This visual analysis is supported by the poor classification results for the Southampton buildings with decision boundaries obtained from the Zurich data (Figure 8). Thus, we conclude that the urban morphology of the Southampton and Zurich region is so different that in general every region has to be classified based on its own set of prototype buildings (i.e. training set). For such a supervised approach a check of the class separability represents a key step for practical applications. The training samples selected by the user have to be validated by the system, e.g. by use of cross validation or boot strapping. Also a visually analysis, for example, with the previously introduced 3-D or 2-D representation can provide directions, assuming that a low dimensional representation is sufficient. Only then can the structure recognition process be continued.

7. Conclusions and Outlook

In this article we described a method to classify buildings into five groups of urban structures. For the approach we hypothesise that the classification approach can be based solely on laws of perception, which enables us to focus exclusively on the geometry of buildings. For the realisation of the classification we defined in a first step a set of basic measures derived from *Gestalt* principles (Wertheimer 1923). Afterwards we utilised PCA to visualise the buildings in the aforementioned feature space. In the third step we developed a classification approach and evaluated several parameters influencing the classification accuracy. In this context, we focused in the experiments on the applicability of different discriminant analysis algorithms, the influence of specific measures, the influence of scale and regional factors of a dataset, and the effect of different buffer sizes used for the density indices.
These experiments illustrate and use at least two fundamental laws of GIScience. On the one hand we assume and use Tobler's Law of spatial auto-correlation (Tobler 1970) on a local scale. To this end, we applied a spatial mode filter to the classified data in a post-classification process to ensure homogeneity among neighbouring buildings. On the other hand we observed during the experiments the law of heterogeneity, which can be identified as the second law of GIScience according to Goodchild (2004). Here again the law shows a scale effect. On a local scale we have to be aware that buildings right across the street can show a completely different urban structure, for example a change from industrial to urban residential area. To respect this large-scale heterogeneity we limit the focus of the spatial mode filter, e.g. to 200 meters. On a small scale, spatial heterogeneity could be discovered when classification results for Southampton and Zurich building data were compared. In our experiments we recognised that the classification of the Southampton buildings based on decision boundaries trained with data from Zurich results in a low classification accuracy because urban structures are manifested differently in both regions. In consequence we should use sample data obtained from the region of interest itself for the training of the decision boundaries to account for the strong regional variation of the chosen measures.
Future work should address in the first place a more detailed assessment of the discriminant analysis algorithms and their parameter settings. Candidates for further parameter analysis are AdaBoost (involving the parameter for the number of decision stumps), the Batch Perceptron algorithm (stopping criterion) and the SVM with parameter γ of the RBF kernel. Having made a decision on a specific discriminant analysis algorithm the next step would be to determine confidence values for the evaluation of certainty. Considering finally the developed 2-D representation to visualise the nine different properties of building structures we can image an enhancement for task specific needs. For instance the visualisation approach could be utilised to enable a comparison of urban morphologies of different cities or to analyse urban development processes in time series.
Our further research will exploit the urban structure information obtained in this paper for automated map generalisation. So called generalisation zones will be used to enable an adaptive generalisation algorithm selection and parameterisation with respect to the urban context. In Figure (1) such generalisation zones based on the structure classes are shown for Zurich. Here the street network has been polygonised to obtain the blocks (zones) and afterwards the urban structure type has been assigned using a majority vote of the building classes inside the block. Now, we are able to implement map generalisation rules such as: <If> a building is too small to be legible on a map <And If> it is in a rural environment, <Then> enlarge the building; because it may be an important object for map user orientation. First experiments that apply such rules for automated building generalisation are reported in (Steiniger and Taillandier 2007).
The application of the classification approach to map generalisation automatically involves considering at least two additional issues mentioned in the discussion. The first is to test classifications with a reduced set of measures, since fewer measures could speed up the processing. This is particularly relevant if tens of thousands of buildings have to be classified at once. The second issue is to analyse scale and generalisation effects of the base data for the classification. But prior to addressing these points the development of detailed application scenarios for map generalisation and a proof of the application concept are primary objectives of our future research. As a final note we should mention that the building classification is accessible as a web service within the WebGen framework (Burghardt et al. 2005) on www.ixserve.de for the *JUMP* GIS (currently offering the Batch Perceptron and the MSE algorithm).

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C. Research Paper 3

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Utilising urban context recognition and machine learning to improve the generalisation of buildings

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The introduction of automated generalisation processes in map production systems requires that the generalisation system is capable of processing large amounts of map data in acceptable time and that the results have a cartographic quality similar to traditional map products. We present two different approaches which should improve current generalisation systems with respect to these requirements, focusing on self-evaluating systems that build on the multi-agent paradigm. The first approach aims to improve the cartographic quality by utilising cartographic expert knowledge. More specifically we introduce expert rules for the selection of generalisation operations based on a classification of buildings into five types, including inner city, urban, suburban, rural, and industrial and commercial buildings. The second approach aims to utilise machine learning to reduce the time in which a good cartographical solution is reached. Both approaches are tested for the generalisation of buildings to the map scale of 1:25 000. An evaluation in terms of efficiency and effectiveness shows improvements, especially for the combined approach which includes expert and machine learnt rules. Problems have been identified resulting from difficulties to formalise cartographic quality by means of constraints for the control of the generalisation process.

Keywords: map generalisation; data enrichment; machine learning; expert knowledge; building generalisation

AMS Subject Classification: 68U35; 68W40

1 Introduction

The number of national mapping agencies that introduce automated map generalisation procedures into their map production workflows is steadily increasing (Stoter 2005). Conventional and automated map generalisation share the same basic objectives, which includes to fulfil the intended map purpose and ensure the map legibility, taking into account user habits and principles of human visual perception. In order to achieve these objectives for automated map generalisation it is necessary to transfer the cartographic knowledge into a machine understandable form. Three types of cartographic knowledge have been identified by Armstrong (1991): a) geometric, b) procedural, and c) structural knowledge. The *geometric knowledge* describes information on the size, shape and topology of map objects and can be obtained by measures applied on the objects' geometry. *Procedural knowledge* describes rules for the selection of appropriate generalisation algorithms in the presence of cartographic conflicts. For instance, if a building is too small to be clearly legible on the reduced scale map (conflict), then the building may be enlarged (algorithm A) or eliminated (algorithm B). Finally, *structural knowledge* covers the cartographic knowledge needed to identify which objects and "structures" are important, e.g. in terms of their cultural, economical or geomorphological meaning. Thus, the structural knowledge influences the decision whether the small building of the above example must be preserved (enlarge building) or whether it is unimportant for the map reader (eliminate building).

In general we aim to distinguish between two alternatives to transfer the cartographic knowledge to the automated process. The first solution is the formalisation of the human knowledge by means of expert rules. Thereby the term rules is used in the sense of: *If (condition) Then (action)*. The second alternative is provided by the application of machine learning techniques which learn rules by statistical inference of actions carried out by the cartographer (or by generalization engines) with reference to the cartographic conditions encountered. Both approaches root in the idea of data enrichment since they evaluate object characteristics for the conditional part of the rule. Neun *et al*. (2004) describe data enrichment as "[a necessary process] to equip the raw spatial data with additional information about the objects and their relationships.[..]". Data enrichment bridges the gap between structural knowledge and procedural knowledge by integrating the information obtained from the preceding step of structural analysis into the following generalisation process (Steiniger and Weibel 2005). This enables an informed decision making for the selection of generalisation operations. Suppose that during the structural analysis stage it has been observed that a minor road ends at a tourist viewpoint. Subsequently the road is marked as a feature that is important for the map reader to access the viewpoint. In the generalisation system, the procedural knowledge has been formalised by rules of which one specifies that "important" roads must not be deleted. Thus the generalisation system will decide, based on the importance flag, to retain the road even if minor roads should not be displayed.

The focus of this work is on revising existing knowledge for the control of the map generalisation processes by utilising both expert rules and machine learnt rules. We concentrate on self-evaluating systems building on the multi-agent paradigm, as these are among those systems that represent the state-of-the-art in automated map generalisation. Our hypothesis is that both types of knowledge revision will help to improve the map generalisation process in terms of efficiency and effectiveness. To test our hypothesis we will specifically examine knowledge for the generalisation of individual buildings for a topographic base map (scale 1:25 000). We start from existing rules that only take into account the internal conflicts of a building in order to decide which generalisation algorithm to try on it next. These rules, the types of cartographic conflicts and the generalisation algorithms for buildings will be introduced in § 2. We will then propose two approaches for modifying the existing rules with respect to the nature of the buildings that are generalised (§ 3). The first approach pursues the idea of introducing expert rules while the second approach utilises machine learning techniques. After having outlined the theoretical framework we describe the experimental setup and present the results (§ 4). We evaluate our hypothesis in terms of efficiency by considering the time necessary to generalise a building. The evaluation with respect to effectiveness considers the cartographic quality of the generalised buildings. Afterwards we discuss the improvements and identified problems (§ 5). We conclude in § 6 by recalling the main achievements and outlining further research objectives.

2 The current approach for building generalisation

Map generalisation systems consist of several logical components. In general one can distinguish between four of them (Ruas and Plazanet 1996, Weibel and Dutton 1998): constraints, measures, algorithms and the generalisation control mechanism. Thereby the control mechanism is responsible for the decision making, i.e. how to generalise, by evaluation of constraints and triggering of generalisation algorithms. In the following sub-sections we will explain these four components with respect to building generalisation.

2.1 Constraints and algorithms for building generalisation

A map should meet two basic objectives. First, the map should be designed to fulfil a specific purpose and second, the map must be legible. While the first objective mainly imposes conditions on the semantics of the map the second objective imposes geometric conditions. To meet both objectives manual map generalisation builds on a few general principles:

- select the relevant content and omit the unimportant (semantic level),
- preserve and emphasise the typical and unusual (semantic and structural level),
- simplify to make the map legible (geometry level).

These principles, while easy to grasp and to apply for a human cartographer, need to be decomposed and reformulated for automated map generalisation. A decomposition is necessary to specify exactly under which conditions a map is “legible”, what is “typical and unusual”, and what is meant by “important”. It further covers the definition of algorithms and their activation conditions for the mentioned actions: select, preserve, emphasise and simplify. The reformulation is necessary to transfer the principles into a *condition–action* scheme. In focusing on the generalisation of buildings we will now attempt to decompose the mentioned principles. Note that “conditions” are also called “constraints” and “actions” are termed “operations” in the generalisation literature (see also § 2.1.3).

2.1.1 Conditions on building representation. Several conditions have been found to be useful to describe the legibility of a map as described by Weibel and Dutton (1998) and by the AGENT Consortium (1998). With respect to buildings the legibility conditions focus exclusively on the geometrical aspects. Commonly six conditions are identified (figure 1): (C1) minimum building size, (C2) building outline granularity, (C3) wall squareness, (C4) minimum inner-width, (C5) minimum distance between two buildings, and (C6) the building density preservation condition. These six conditions are also called active conditions since they can trigger a generalisation operation if they are not fulfilled. Opposed to active conditions are passive conditions. Such conditions are used to prevent strong changes resulting from generalisation actions activated by the previously listed conditions. With respect to a single building we identified three passive conditions. The first condition is intended to prevent strong changes of the building shape and is called concavity condition (C7, Bard 2004). The second condition (C8) is called positional accuracy and should prevent that a building’s position is changed too much during building displacement. Such a displacement operation may be triggered due to a violation of the minimum distance condition between buildings. Finally, a third condition for individual buildings that we denote as conservation condition should prevent the elimination of important buildings (C9). This last condition demands a definition of importance on a structural or semantic level. For instance, hospital or school buildings are often considered an important type of building due to their unique function and their different geometrical characteristics compared to other buildings in a residential district.

In the remainder of this paper we will call the violation of a condition a *cartographic conflict*.

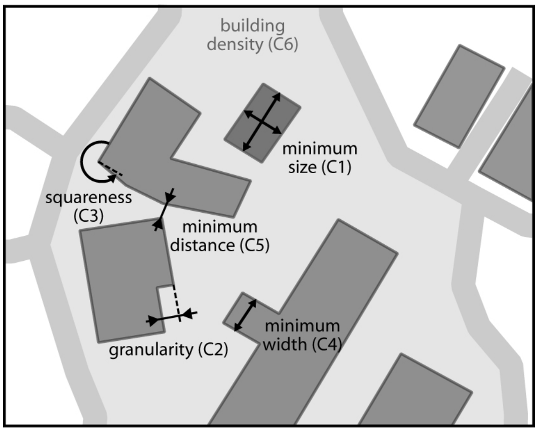


Figure 1. Active conditions acting on buildings.

2.1.1 Actions for building generalisation. Several actions can be activated if one of the previously listed conditions is violated. An extensive listing of actions, so called generalisation *operations*, to meet the legibility conditions is proposed by McMaster and Shea (1992). For the generalisation of buildings, those actions focus either on the elimination or the geometrical transformation of buildings. Note that in automated generalisation a particular cartographic operation, e.g. building displacement, can be realised with different algorithms which are based on different solution approaches. A list of generalisation algorithms that deal with the above conditions is given in table 1.

Table 1. Algorithms for building generalisation.

Generalisation Algorithm	Applicable to following conditions/ constraints:	Author
A1) Scale polygon	C1	---
A2) Simplify building outline	C2	Regnauld et al. (1999)
A3) Building wall squaring	C3	Regnauld et al. (1999)
A4) Enlarge width locally	C4	Regnauld et al. (1999)
A5) Simplify to rectangle	C2, C3, C4	AGENT Cons. (1999b)
A6) Enlarge to rectangle	C1, C2, C3, C4	AGENT Cons. (1999b)
A8) Building typification	C5, C6	Burghardt and Cecconi (2007), Sester (2005)
A9) Building displacement	C5	Ruas (1998), Bader et al. (2005)

A violation of passive conditions does not necessarily result in an activation of a specific operation or algorithm. In operational generalisation systems such conditions either simply trigger a recovery of the initial state prior to generalisation (termed backtracking) or flag the result as invalid.

2.1.3 Reformulation of generalisation principles. As pointed out previously we need to formulate the relation between actions and conditions in a machine understandable format in order to render it amenable to automation. For this purpose two general approaches exist. One approach is to use *rules*, with the well known scheme *If (condition is true) Then (action A) Else (action B)*. The important point to note here is that after evaluation of the condition an action is always triggered. In the second approach, the so called *constraint-based approach*, an action does not necessarily follow a condition, at least not immediately. This approach has been introduced to automated map generalisation by Beard (1991) and has since been widely accepted as a standard approach for modelling the generalisation (Harrie and Weibel 2007). One property of the constraint-based approach is that several cartographic conditions (here called constraints) can be evaluated first, and afterwards it will be decided on the best action to solve a given problem. This procedure is especially of value if conditions contradict each other such as C5 (minimum distance), and C8 (positional accuracy). To achieve a solution every condition (a *constraint*) proposes none, one or several actions to solve a given problem. After all existing constraints have been evaluated, a ranking of all proposed actions is established and finally the most promising action is triggered. The modelling approach we will follow in our work is the constraint modelling approach. Thus, all the conditions listed in the preceding section can be denoted as constraints.

A question still left unanswered is how we know whether a constraint is fulfilled or not. Every condition is associated with a measure, which returns a quantitative value for a geometrical or topological property of one or more map objects. This value is mapped into a qualitative statement, the so called *satisfaction*, by comparing them to a reference value, e.g. the minimum building size for a particular target scale and map purpose. The qualitative statements can be expressed either as Boolean (true/false), integer scores (e.g. 1 to 5) or continuous floating point scores (e.g. 1.0 to 5.0), using different mapping functions (Bard 2004). In our experiment we will use continuous scores in the range of 1.0 = *constraint violated* to 10.0 = *constraint fully satisfied*.

2.2 Controlling generalisation with an agent model

In contrast to the rule-based approach where an evaluation of a condition follows an immediate action the constraint-based approach requires an inference machine to decide which action follows next, if any. Two general models for the decision making should be distinguished here for an automated approach. In the first model the human has control over the decision making processes at all times and does explicitly define the association between conditions and actions and their order of processing. Such an approach can be realised using workflow models, for instance described in Petzold *et al*. (2006). In the second model cartographic knowledge is stored in the system in terms of constraints, operations and associations between those. Here, the system itself infers decisions from stored knowledge (i.e. associations) and the evaluation of the constraints. Such an approach, based on previous work by Ruas (1999), is described in Barrault *et al*. (2001) and Ruas and Duchêne (2007). This approach uses the multi-agent system paradigm.

In our experimental part, we will utilise this agent approach and hence explain it in more detail. As we focus on building generalisation every building will be modelled as an agent. In agent-based modelling the term "*plan*" is used to denote an action that can be executed by an agent to attain his "goals". In automated map generalisation such a plan consists of a generalisation algorithm plus parameter settings, and goals corresponds to cartographic constraints. In this model one assigns the building agent the legibility constraints which it must fulfil. The process scheme of the generalisation of such a building agent, the so-called

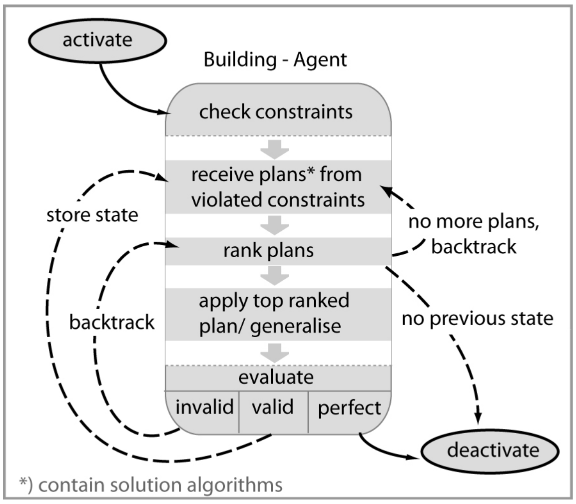


Figure 2. Generalisation procedure of a building in an AGENT system – modified after Barrault *et al*. (2001).

agent lifecycle, is shown in figure 2. This process realises a "trial-and-error" approach, essentially mimicking the work style of a cartographer. Every time a plan (i.e. a generalisation algorithm) is applied this is seen as one trial that results in a new agent *state*. In last step of a single lifecycle the states are evaluated and classified into "valid", "invalid" or "perfect" states. For each state, the so-called *happiness* is calculated as a weighted average of the constraint satisfaction values over all constraints. A state is usually considered as *valid* if the happiness or the satisfaction of the constraint that proposes the acted plan has improved compared to a previous state. For the other cases the state is considered as *invalid*. A state is classified as *perfect* if all constraints are satisfied (no violation). In the latter case the generalisation of the building is terminated while for the other two cases the state is stored and the generalisation process continues with a new trial. For a valid state the process continues from the current state, whereas for an invalid state the system will return to a previous valid state and continue from there. In both cases finally, that is after all plans are tried, the system will select the generalisation solution which best fulfils all constraints (i.e. has the highest happiness value) of all stored solutions. Such a trial-and-error generalisation process is depicted as a process tree for one building in figure 3.

To conclude this section, we aim to discuss the parameters used for controlling the generalisation process in the agent model. The first parameter is called *importance* and is used to calculate the happiness, weighting constraints against each other. The second parameter, *priority*, is used to determine in which order constraint violations should be solved. Defining an appropriate order is useful since the preceding solution of one conflict may involve an easier solution for a second conflict. For instance, if a minimum size conflict (C1) is solved first by building enlargement, then a previously detected minimum width conflict (C4) could have been solved at the same time. Finally, giving individual *weights* to a plan is necessary to define which plan should be acted before another plan proposed by the same constraint. As a rule one can say that a plan which results in less (geometrical) changes is preferred. All three parameters are usually pre-defined by an expert but may also be set dynamically at runtime (e.g. for the priority parameter see Ruas 1999). For a more detailed introduction of multi-agent models in cartographic generalisation we refer to the review by Ruas and Duchêne (2007).

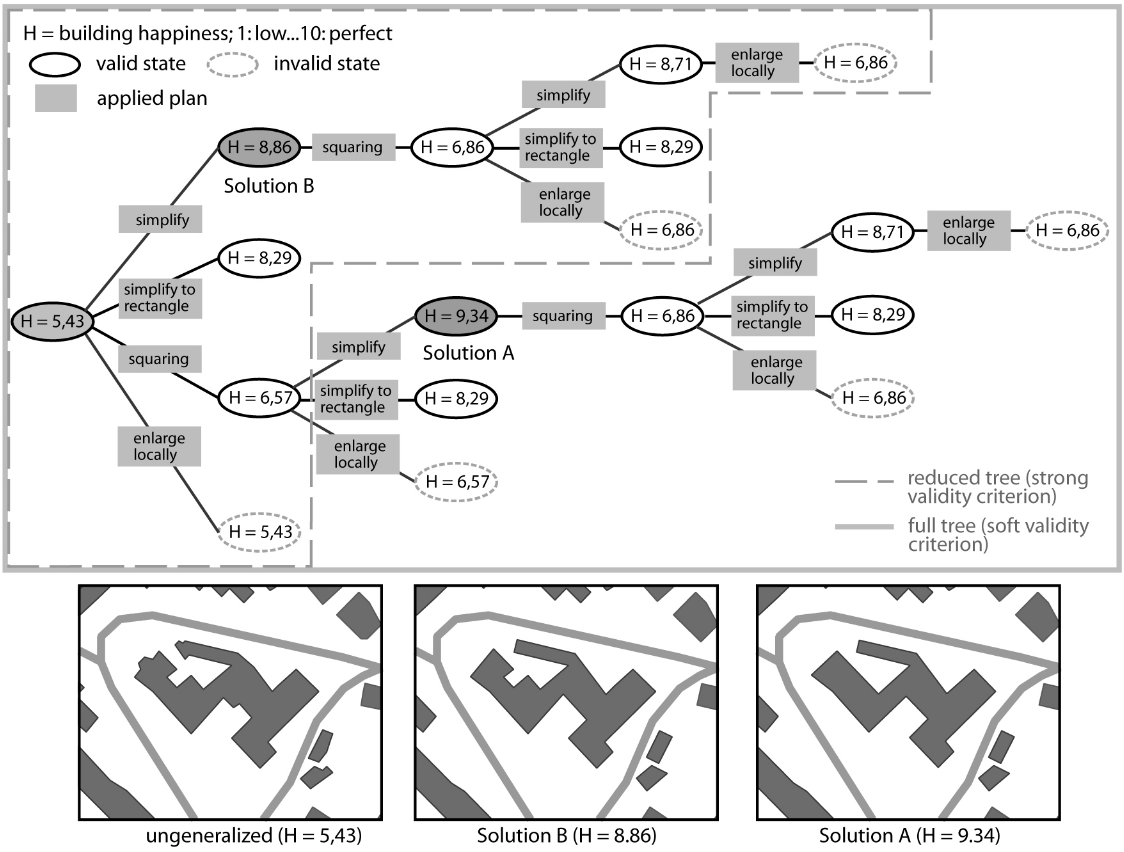


Figure 3. Search tree of possible generalisation solutions for one building. The best solution is A, corresponding to a high happiness value close to 10.0. It is normally selected as the final solution. In § 3.1 we explain under which circumstances solution B is selected as the final solution.

3 How to improve building generalisation

In the previous section we have introduced an approach for the generalisation of buildings which is based on constraint modelling and the use of a multi-agent system to control the generalisation process. We further listed the constraints necessary to ensure map legibility and algorithms for resolving cartographic conflicts. In this section we aim to introduce two new approaches for the improvement of knowledge applied in the process control. Both approaches are based on a better formalisation of cartographic knowledge through knowledge acquisition. After discussing the possibilities for an improvement in the first sub-section, the second and third sub-section will describe the two approaches for knowledge acquisition. The first method extracts information from buildings by classifying them into urban structure classes. These classes are later related to expert rules for the process control. The second method describes a machine learning technique for the direct extraction of rules for controlling the generalisation process.

3.1 Deficiency of the current approach and improvement possibilities

As outlined in the introduction we aim to improve the current generalisation approach in two respects. On the one hand we focus on making the system more efficient while on the other hand we want to raise the effectiveness. Therefore it is necessary to analyse the current approach to generalisation process control.

The disadvantage of the trial-and-error approach is that it is very exhaustive. If one analyses the tree in figure 3, it becomes obvious that the tree contains redundancies (the same sub branch exists two times) and a good number of the branches ends with unsatisfactory and invalid solutions. Thus, in both cases processing efforts could be reduced, and *efficiency* increased, if either 1) stronger validity and termination criteria are applied, or 2) the list of available plans, or the plan selection respectively, is better controlled. We aim to try both methods in our experiments. For the first approach we aim to utilise machine learning techniques by identifying rules to infer the validity and the termination criterion in specific situations. A dynamical, context-dependent setting is necessary since a static validity criterion, used for all buildings, may result in cases in which the best solution is missed (in figure 3 solution B instead of A). For the second approach, involving the control of the plan list and plan selection, we aim to apply expert rules and machine learnt rules. In both cases we will allow only plans to be proposed which are appropriate for the specific cartographic context of a particular building.

Improving the system in terms of *effectiveness* is as well related to the proposal of plans adapted to the spatial and semantic context of map objects. But here we like to obtain a graphically more convincing solution which should theoretically correspond to a higher number of satisfied constraints, hence higher values of happiness. Thereby a smaller set of trials will probably be a side effect of the adaptation to the context. An improvement in effectiveness is possible by introduction of expert rules. Note that the use of expert rules may result in improvements which we may not be able to evaluate quantitatively, as these improvements relate to conflicts that are not represented or measured by our set of constraints. A gain in effectiveness is also possible with machine learnt rules. However, this holds only if the rules are learnt from a comprehensive solution tree (i.e. with a weak validity criterion), while the reference generalisation system applies a strong validity criterion.

3.2 Context analysis and building classification

Our objective is to transfer the cartographic expert knowledge into the domain of automatic building generalisation. This can be accomplished, for instance, by trying to extract higher order semantic concepts from the map data that are not directly represented but can be made explicit with pattern recognition techniques. A condition for the extraction of such higher order semantic concepts is that they represent a cartographically useful concept. In our case this includes on the one hand that the concept(s) can be related to cartographic map generalisation rules, while on the other hand the concept must be intuitive to understand and have a utility for the average map reader. Based on the analysis of the generalisation literature (e.g. SSC 2005) and the study of topographic maps as well as maps for urban planning and education, such useful concepts have been identified by us with respect to the urban fabric. More specifically we identified a cartographically useful classification of buildings into five urban structure classes, which are: (1) inner city buildings, (2) industrial and commercial buildings, (3) urban buildings, (4) suburban buildings and (5) rural buildings. The pattern recognition method, here a supervised classification approach, is extensively described in Steiniger *et al*. (in press) and its use as a web-processing service in Neun *et al*. (in press). The result of the classification process for a dataset of Zurich (Switzerland) is shown in figure 4. The classification accuracy reached is 82 percent (kappa statistics: 0.73).

Once classified, every building can be related to its (urban) context. Based on this information, we are able to introduce rules in the generalisation system that trigger specific generalisation algorithms and algorithms sequences that are tuned to the specific urban context class (see below in § 4.1.2). This should avoid unnecessary generalisation trials and achieve better cartographic quality.

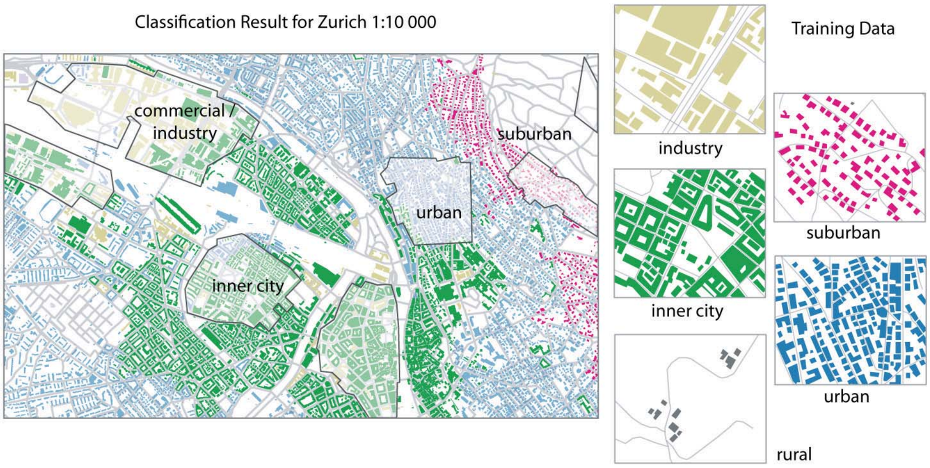


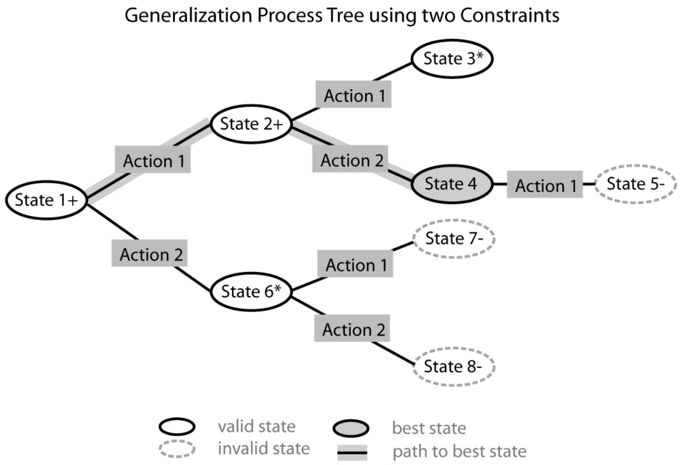
Figure 4. Classification results for the Zurich building data. The lighter areas mark the training data. (Data courtesy of Geomatik + Vermessung, City of Zurich).

3.3 Learning rules with machine learning techniques

3.3.1 What we aim to learn. To improve the efficiency of the generalisation system, we would like to learn rules of the following structure: *If* (*building_size* < 200 m^2) *And* (*building_type* = inner_city) *Then* (privilege *building_elimination_plan*). The advantage of such rules is that they are easy to interpret and subsequently also useful to evaluate existing knowledge of the generalisation system. With the aim to learn interpretable rules that increase efficiency we continue work by Plazanet *et al*. (1998) and Mustiere (2005) who used learning techniques for road generalisation, and work by Dyèvre (2005) and Ruas *et al*. (2006) who use rule learning for building generalisation. In our specific case, three different rule types should facilitate the following actions: 1) *Choosing a branch (of the search tree)* – The first rule type is called *priority rule* and helps to identify the constraint which should be solved next to faster converge to an optimal solution. Thereby an optimal solution is reached if all building constraints are satisfied. Thus, this type of rules will try to minimise the number of tested solutions and subsequently the size of the search tree in figure (3). 2) *Avoiding a branch* – The second rule type is called *validity rule* and is used to identify situations in which it is likely that no acceptable (invalid) solution is obtained if one proceeds with the current generalisation result. Such rules help to avoid unnecessary generalisation tries. 3) *Terminate process* – Finally the third type of rules to be learnt are *termination rules*. They identify situations in which the generalisation process should be terminated prematurely since obtaining better solutions in terms of a higher happiness value is unlikely. Thus, the number of generalisation tries is limited by these rules.

3.3.2 General learning method. In the artificial intelligence and data mining community several rule learning approaches have been developed (Hand *et al*. 2001, Witten and Frank 2005). For our purposes we will use a supervised rule learning approach, which means that we will have to provide training samples to the learning algorithm. The approach follows the general three phase learning scheme:

1. *Exploration step* - This step consists in logging the actions of the generalisation process for a large number of geographical objects. During this phase, the process uses the procedural knowledge initially contained in the generalisation system. The logs record the whole information related to successes and failures of the various actions invoked by the system, and hence of the procedural knowledge it contains.



Constraints: C1: proposes action 1
C2: proposes action 2

Training Sets

State	Validity	Stop Criterion	Priority
1(+)	(S1,valid)	(S1,continue)	(S1, C1: priority) (S1, C2: no priority)
2(+)	(S2, valid)	(S2, continue)	(S2, C1: priority) (C2, C2: no priority)
3(*)	(S3, invalid)	not used	not used
4	(S4, valid)	(S4, stop)	not used
5(-)	not used	not used	not used
6(*)	(S6, invalid)	not used	not used
7(-)	not used	not used	not used
8(-)	not used	not used	not used

(+) on path, (*) related to path, (-) not on path

Figure 5. Examples of training sets built from a generalisation search tree for one building.

2. *Analysis step* - This step is comprised of analysing the logs obtained during the previous phase and in deducing new knowledge from it. Thus, the training samples are selected from the database generated in the analysis step and afterwards the rules are learnt from these samples.
3. *Exploitation step* – The third step involves testing the system with the previously obtained rules on a second dataset with so-called validation samples. If the rules previously learnt do not match this validation dataset, then these rules are discarded and steps 1-3 repeated.

We will describe the two parts that are essential for our experiments, that is, the creation of the training samples and the generation of rules, in the next sub-section.

3.3.3 How rules are learnt: training samples selection & analysis method

- *Selection of training samples* – For the rule learning it is necessary to define from which kind of data the rules should be learnt. In the case of supervised learning every sample of the training data must consist of a description vector that is used to define the condition, and a label that corresponds to the action. For our purposes we will use the constraint satisfaction of every state as description vector. The labels will be defined according to the rule type which should be learnt (priority rules, validity rules, and termination rules). Furthermore we restrict the selection of training samples to those states which are directly related to the best (successful) path to the final solution. This definition allows to obtain a correct state characterization and at the same time is not too complex for the learning procedure. In figure 5 we give an example that shows which states of the generalisation process of one building are used for the training. Obviously, however, the final set of training data used as input for the rule learning algorithm will consist of samples obtained from several dozens of buildings, and not only from one.
- *Learning rules* – One approach for an (association) rule learning algorithm is to scan the dataset for frequent patterns in which a component of a description vector occurs together with a specific label. Suppose that the pattern (*building_size_constraint* satisfaction = 4) and (applied plan is *enlarge_building*) appears 20 times in the training dataset and in 80% of the cases the label value is *valid,* while for the remaining 20% the label value is *invalid*. Thus, we can use the information *building_size_constraint* satisfaction = 4 to predict that the plan *enlarge_building* will be a successful operation with a probability of 80 %. To build the rule base it is

necessary to define an occurrence threshold (e.g. the pattern should at least appear 10 times) and further a significance threshold (e.g. 8 of 10 patterns lead to the same prediction, e.g. a *valid* plan). For the experimental part we used the approach of exception-based rule learning that is thoroughly described in the text book by Witten and Frank (2005).

4 Experiment

4.1 Experimental setup

4.1.1 Target map scale and derived constraint settings. For the experimental part we decided to focus on the generalisation of buildings for the base map of scale 1:25 000, starting off from data at a nominal scale of 1:10 000 to 1:15 000 (cf. § 4.1.3). Focusing on such a large scale has the advantage that only few buildings need to be eliminated (Müller 1990) and only few displacement operations due to overlaps between buildings and between buildings and roads are necessary. Thus, complex operations such as building typification for dense built-up areas need not be considered and it is easier to evaluate the effects of the expert and learnt rules. Hence, the set of constraints that we applied involves only the following constraints for individual buildings: C1 – minimum size; C2 – granularity; C3 – squareness; C4 – minimum width; and C7 – concavity. The minimum distance constraint is not applied due to two reasons: On the one hand displacement operations can be executed after the previously mentioned constraints are satisfied. On the other hand, if the generalisation of one building is influenced by the generalisation of its neighbour buildings it is harder to identify emerging knock-on conflicts due to geometry transformations. In table 2 the constraints, their parameter settings and the plans (i.e. generalisation algorithms) that are proposed if a constraint is violated are listed. We adopted the parameters and plans as developed by experts during the two projects AGENT (Barrault *et al*. 2001) and Nouvelle Carte de Base (NCDB, Lecordix *et al*. 2006), with small modifications. The parameters (thresholds) listed have different meanings. For instance *minSize*, *delSize* and *medSize* are used to ensure a minimum building size (constraint C1). Based on a comparison with the threshold *delSize* and *medSize* it is decided whether a building will be eliminated or enlarged to meet the minimal size condition (*minSize*). Tolerance values, such as the one for *minEdge*, introduce flexibility regions. For instance if the length of a building wall is 6.0 m (the threshold *minEdge* was set to 6.25 m), then the building is not generalised with a simplification algorithm, due to the length tolerance of 0.5 m. Since we assume that the settings and proposed plans of the constraints C1 to C4 are intuitive to understand we will only explain the settings for the defensive constraint C7 – concavity.

Constraint C7 should ensure that geometric transformations applied to one building do not change the building shape in an unacceptable way. Therefore the ratio of the area of the original building to the area of its convex hull is computed, and the ratio values before and after generalisation are compared (Bard 2004). In table 2 it can be seen that the constraint C7 has a low priority, a high importance and does not propose any plans. The value for the priority parameter is low since priority proposes no plans. If the change of the building outline is too strong it is desired that the solution is rejected, and either another plan is applied or the building is flagged for subsequent interactive generalisation. A rejection is achieved in that the high importance value combined with a low concavity constraint satisfaction will result in a lower happiness value for the building than before. The lower happiness value will then prevent that this state is selected as the best solution, since other states (even the initial state) should have higher happiness values.

Table 2. Constraints used in the experiment for the scale change to 1:25 000 used for the reference building generalisation. Settings are similar to the Nouvelle Carte de Base project (NCDB, Lecordix *et al*. 2006).

Constraint	Constraint type	Priority (1:last ... 5:first)	Importance (1:low ... 5:high)	Default settings		
				Plan / action	Condition for plan proposal (with plan weight w)	Threshold values for 1:25 000
Minimum size (C1)	active	5	5 (NCDB: 4)	A1: scale polygon A6: enlarge to rectangle A7: eliminate	IF { area ≤ *delSize* THEN A7 (w=1)} ELSE IF { area > *medSize* THEN propose A1 (w=2) and A2 (w=1)} ELSE { A1 (w=1) and A2 (w=2)}	*minSize*: 80m^2 *delSize*: 20m^2 *medSize*: 60m^2
Granularity (C2)	active	4	5	A2: simplify A5: simplify to rectangle	IF area ≤ *minSize* THEN propose: A5 (w=2) and A2 (w=1) ELSE propose: A5 (w=1) and A2 (w=2)	*minEdge*: 6.25m *minSize*: 80m^2 tolerance for *minEdge*: 0.5m
Squareness (C3)	active	4	4	A3: squaring	proposes A3 (w=1) if violated	*delta*: 10° tolerance: 0.5°
Minimum width (C4)	active	3 (NCDB:4)	3 (NCDB:5)	A4: enlarge width locally	proposes A4 (w=1) if violated	*minWidth*: 6.5m tolerance: 0.5m
Concavity (C7)	passive	1	4	---	---	tolerance: 0.15

4.1.2 Expert rules introduced. The settings of table 2 are used to obtain the reference generalisation results for the comparison with the results gained with expert rules and learnt rules. The learnt rules which we introduce to the generalisation system are presented in the results section (§ 4.2) since they are derived from a generalization run with the settings given in table 2. In contrast, the modifications of the settings and plans of table 2 evolving from expert rules are conceptual and presented in table 3. With these context-dependent rules we aim to realise the following cartographic considerations: Industrial and commercial buildings should not be squared since the building sizes tend to be large and are adapted to the previously existing infrastructure. This affects also the possibility to simplify buildings to a rectangle, since a representation as a block is on the one hand inadequate with respect to their often complex shape and on the other hand may result in overlaps with other infrastructure objects (roads and buildings). Similar considerations exist with respect to inner city blocks. Usually the individual buildings forming a block adapt to the nature of the topography and the existing infrastructure. Specifically in (European) old towns where the urban fabric has been shaped over centuries straight shapes of building blocks are rather unusual as it can be seen in the Zurich dataset presented below (figure 6, old town on the lower left side). An additional rule applied to the inner city buildings is to eliminate unimportant small buildings to strictly retain free space for necessary building enlargement and displacement operations. Assuming that in suburban areas residential districts dominate, consisting of individual and rather small buildings, we propose to enforce the plan which simplifies small houses to rectangles instead of trying out time consuming building wall by wall simplification, followed by an enlargement operation. This assumption is also applied to buildings in the rural context. A second objective for rural buildings is to preserve even small buildings as far as possible, since they may be an important point for the map reader's orientation, e.g. if the map is used for hiking.

From the above considerations and table 3 it can be obtained that no specific rules are introduced for urban buildings. Thus, they are handled with the modified reference settings of the NCDB project. To all other urban context classes we have been able to assign specific rules. Hence, every urban context class has its own, cartographically justified set of rules.

Table 3. Expert rules accounting for the specificities of five urban context classes which are applied to the settings of table 2. The proposed changes are explained in § 4.12.

Constraint	Contextual application rules				
	Industry and commercial	Inner city	Urban	Suburban	Rural
Minimum size (C1)	---	1. Set *delSize* to *minSize* 2. Don't propose Enlarge to rectangle (A6)	---	Set weight of Enlarge to rectangle (A6) higher than for Scale polygon (A1)	1. Don't propose Eliminate (A7) 2. Set weight of Enlarge to rectangle (A6) higher than for Scale polygon (A1)
Granularity (C2)	Don't propose Simplify to rectangle (A5)	Don't propose Simplify to rectangle (A5)	---	---	Set weight of Simplify to rectangle (A5) higher than for Simplify (A2)
Squareness (C3)	Don't propose Squaring (A3)	Don't propose Squaring (A3)	---	---	---

4.1.3 Test data, generalisation system and learning framework. For the experimental part we used two datasets. The first dataset from Switzerland (*AV-Light*) contains building data from the Region of Zurich with a resolution corresponding to a 1:10 000 map scale. The buildings have been classified according to the approach described in Steiniger *et al*. (in press); see also § 3.2 and figure 4. In a preceding step before the generalisation buildings touching each other were merged to one building.

The second dataset contains buildings from the region of Orthez in France and has been extracted from the IGN BD-Topo® database. The French data have a resolution of about 1 m corresponding to a map scale of roughly 1:15 000. The building data are pre-classified with a modified classification approach of Boffet (2001), which is better adapted to the French data than our general approach. To use this existing context classification we applied a mapping between the – partially similar – concepts, given in table 4. For the French data a merge operation for touching buildings has been applied as well if the buildings are of similar function type.

Table 4. Mapping from the urban context classes given for French BD-Topo® data to the classes used for the expert rules of table 3.

French urban context classes after Boffet (2001)	Mappings to urban context classes used in Steiniger *et al*. (accepted)	Note
Centre Ville	Inner City	---
Divers	Urban	Sometimes Inner City or Industrial and Commercial may also be appropriate
Fermé	Suburban	Sometimes rather Rural
Lotissement	Suburban	---
Peri urbain	Urban	Sometimes rather Suburban
Unitaire	Rural	---
Activité	Industrial and Commercial	---

For the generalisation of the buildings we used the commercial map generalisation system *Radius Clarity*™ by 1Spatial (2007). This software has been developed from the prototype of the AGENT project (Barrault *et al*. 2001) and the inference machine used can be adapted to the expert and learnt rules. We applied generalisation algorithms which are delivered with *Radius Clarity*™ to explore potential algorithmic deficiencies of the commercial system for further experiments. As mentioned previously the system does not explore the full tree of possible generalisations for a building in order to avoid redundant search (figure 3). The generalisation of an object or situation in *Radius Clarity*™ is valid: If 1) the constraint satisfaction of the constraint proposing the plan has improved, AND 2) at least one of the constraint satisfaction values for the current solution (state) has improved compared to every previously generated solution.

For the learning of the rules we used the OpenSource learning framework *WEKA* (Witten and Frank 2005). More specifically, we applied for the experimental part the *RIDOR-IREP* algorithm that realises an exception-based rule learning approach. Here, the *RIDOR* (RIpple-DOwn Rule learner; Compton *et al*. 1991) is used to establish and manage the knowledge base of learnt rules while *IREP/RIPPER* (Cohen 1995) generates the (exception-) rules.

4.2 Results

4.2.1 Rules learnt. In the machine learning part of the experiment we concentrated on obtaining rules from the analysis of the course of the happiness function, which is calculated as a weighted average of the building constraints used. For the learning of the rules we used 288 buildings as training data from the Zurich sample dataset which contains 724 buildings (figure 6). As described in § 3.3.1 we learnt three types of rules: 1) priority rules, 2) validity rules, and 3) termination rules. All rules learnt for the Zurich data are listed in table 5. As can be seen two of the termination rules (rules 7 and 8) not only account for the evaluation of the constraint satisfaction but also for urban structure types. Thus, a first hint is provided that the introduction of the urban structure concepts helped to better characterise the buildings, which in effect may increase generalisation efficiency.

Table 5. Rules learnt from a test generalisation of buildings from the Zurich dataset (figure 6, middle image). A satisfaction value of 10 corresponds to a fully satisfied constraint.

	Rules for automated setting of constraint priority
Rule 1	IF (*minimum size* satisfaction ≤ 9.5) THEN constraint to solve next = *minimum size*
Rule 2	IF (*minimum size* satisfaction > 9.5) AND (*granularity* satisfaction ≤ 7.5) THEN constraint to solve next = *granularity*
Rule 3	IF (*minimum size* satisfaction > 9.5) AND (*granularity* satisfaction > 7.5) AND (*minimum width* satisfaction > 7.5) THEN constraint to solve next = *squareness*
Rule 4	IF (*minimum size* satisfaction > 9.5) AND (*granularity* satisfaction > 7.5) AND (*minimum width* satisfaction ≤ 7.5) AND (8.5 ≥ *squareness* satisfaction > 5.5) THEN constraint to solve next = *squareness*
Rule 5	IF (*minimum size* satisfaction > 9.5) AND (*granularity* satisfaction > 7.5) AND (*minimum width* satisfaction ≤ 7.5) AND {(*squareness* satisfaction ≤ 5.5) OR (*squareness* satisfaction > 8.5)} THEN constraint to solve next = *minimum width*
	Rules for checking the validity of transformation
Rule 6	IF (*squareness* satisfaction = 10) AND (*concavity* satisfaction ≤ 5) THEN *invalid* state
	Rules for terminating the generalisation of a building
Rule 7	IF (*type* = *industry & commercial*) AND (*minimum size* satisfaction = 10) AND (*granularity* satisfaction = 10) THEN *stop*
Rule 8	IF (*type* = *inner city*) AND (*minimum size* satisfaction = 10) AND (*granularity* satisfaction = 10) AND (*minimum width* satisfaction = 10) THEN *stop*
Rule 9	IF (*squareness* satisfaction = 10) AND (*minimum size* satisfaction = 10) AND (*granularity* satisfaction = 10) AND (*minimum width* = 10) THEN *stop*

4.2.2 Effectiveness – cartographic quality. An evaluation of the improvement in cartographic quality due to the introduction of urban context rules (i.e. the expert rules) is done by visual inspection; not in a quantitative manner. This is justified by the fact that we are not yet able to sufficiently formalise (carto-)graphical quality. An improvement in quality for the rules inferred by machine learning is not possible, since these rules are derived from analysing the values of constraint satisfaction for the reference generalisation. So, cartographically speaking, nothing should change; only the efficiency will improve as better search heuristics are used. Figure 6 shows the generalisation results for a part of the Zurich data. As previously mentioned we did not apply displacement operations to make the identification of problems easier. Thus, overlaps between buildings and roads are possible. A comparison of the result for the reference settings of table 2 (middle image) with the urban context dependent control settings (expert rules) shows that especially for inner city and industrial & commercial buildings the cartographic quality is preserved. More specifically with the reference settings in a number of cases the system proposed the simplification to a

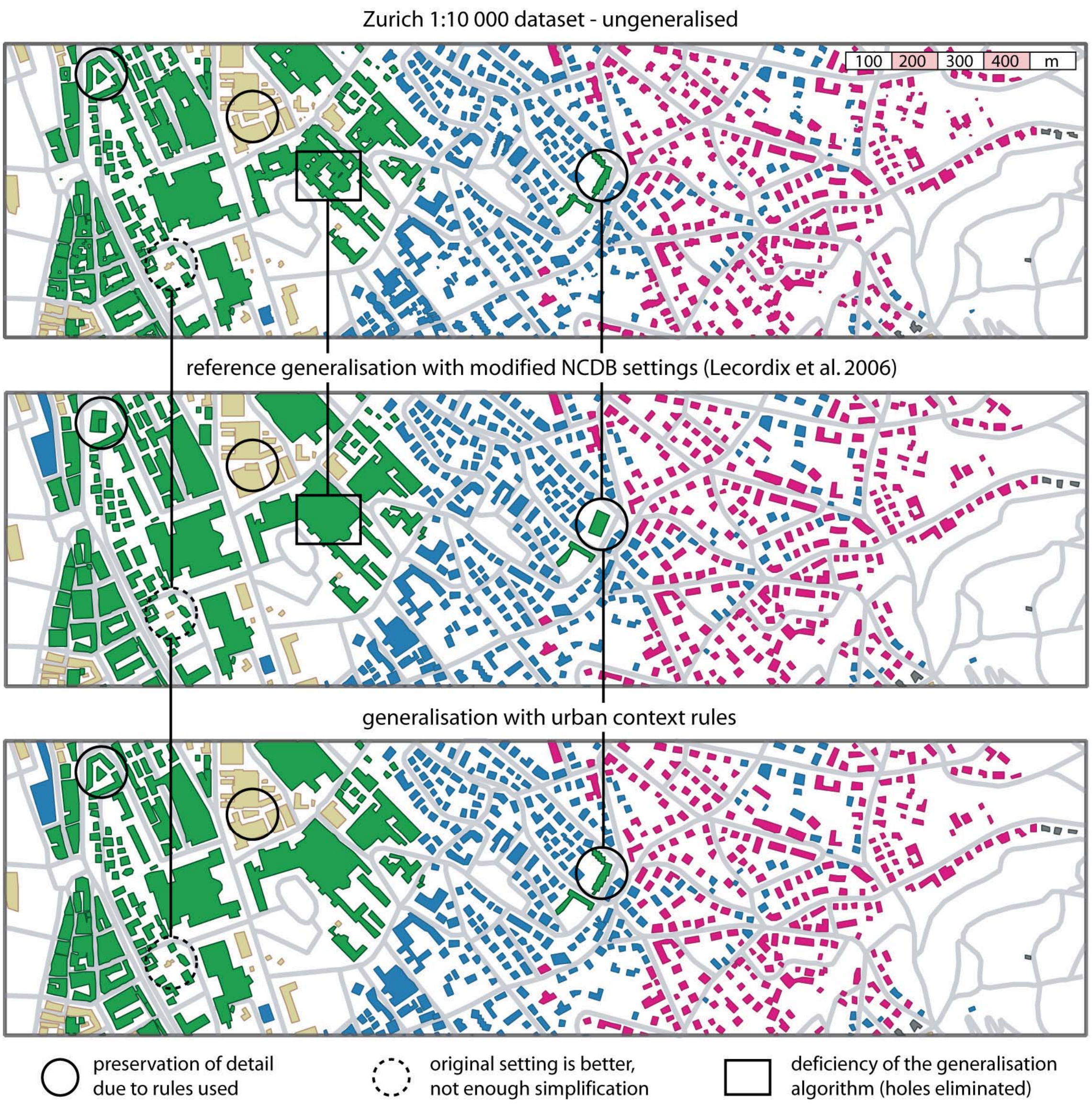


Figure 6. Generalisation results for 1:25 000 map scale for a sample of the Zurich building data. Note that no displacement operation has been used. (Data courtesy of Geomatik + Vermessung, City of Zurich)

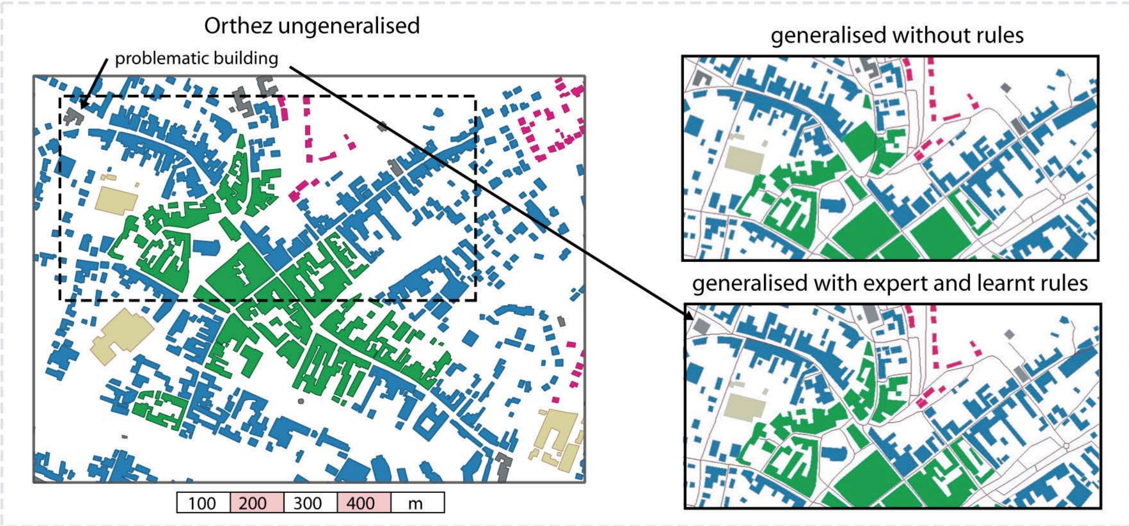


Figure 7. Generalisation result for a selection of the French BDTopo® data showing parts of the town of Orthez. Generalisation map scale is 1:25 000. Different colours correspond to the 5 urban classes. Data reproduced by permission of IGN France.

rectangle resulting in overlaps with streets and nearby buildings. Such cases are now avoided with the urban context rules. A disadvantage of the introduced rules is that in some cases too much detail of the buildings is retained (see dashed circle in figure 6). Deficiencies of the simplification algorithm can be recognised as well. Often courtyards are not preserved although they are large enough for visualisation (see black rectangle in figure 6).

A negative effect with respect to cartographic quality appears for the application of the machine learnt rules, which can be seen in figure 7. In some cases the learnt rules propose the simplification of buildings to rectangles although the loss of detail is not acceptable from a cartographic point of view. Fortunately in most of these cases this happened for rural buildings only. Thus, such strong simplifications could often be avoided by introducing a new rule for rural buildings.

4.2.3 Efficiency – processing speed. To evaluate whether the efficiency increased when rules are applied we created some statistics for the generalisation process with respect to a) the number of generalisation tries for one building, b) the necessary time to generalise a building, and c) the average happiness. Figure 8 shows the statistics for the Zurich and Orthez buildings. Average values for the generalisation without rules (i.e. the reference), with expert rules and the combination of expert rules with machine learnt rules are given. To differentiate between the number of solutions and the processing time is useful because different generalisation algorithms require different time for the computation. Hence, the same number of solutions does not necessarily result in the same time for the overall generalisation process. For instance, the simplify algorithm (A2) is a comparatively time consuming algorithm since it generalises every building wall separately. If the algorithm is avoided the efficiency with respect to processing time will improve whereas the number of tried solutions can still remain the same.

As we can see from the statistics in figure 8 for the Zurich data it is possible to achieve a time reduction by approx. 15% for the expert rules, a similar reduction for the learnt rules, and a reduction by about 45% for combined expert and learnt rules. For the Orthez dataset the reduction in processing time is not significant for the expert rules (approx. 1 %) but still good for the combination of rules (approx. 30%). We see a reason for these different results for the two dataset in the proportion of contextual generalised buildings compared to the reference

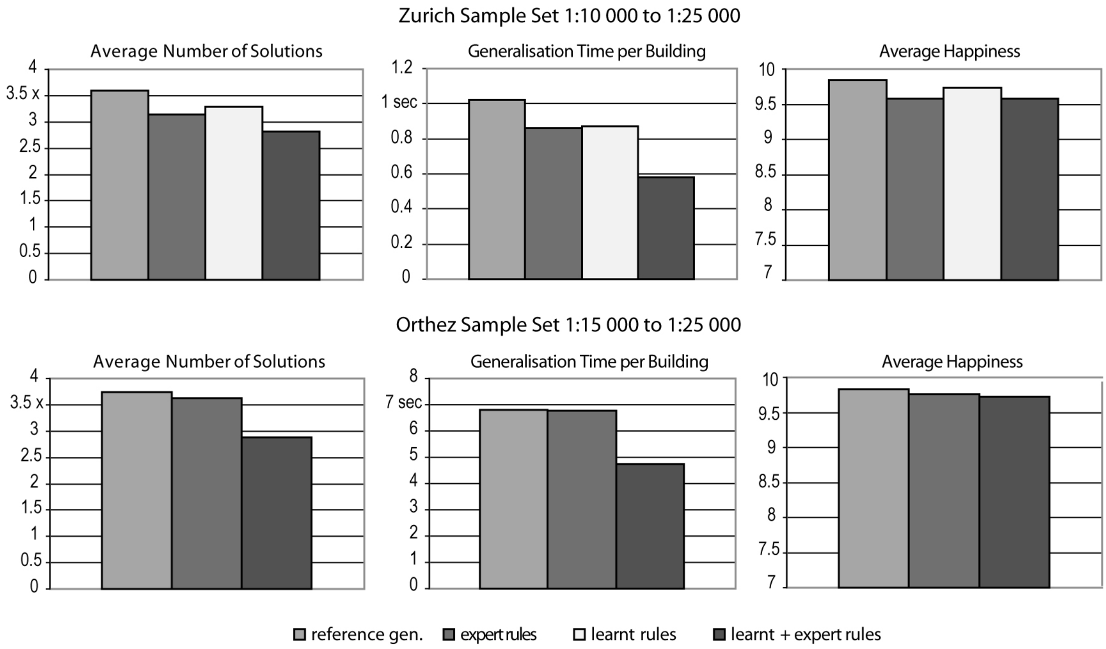


Figure 8. Statistics for the generalisation of the Swiss Zurich data and the French Orthez data. Note that the generalisation times for both datasets are not comparable due to their different data volume.

generalisation. For instance the fraction of inner city and industrial buildings is for Zurich 21% and for Orthez only 6%.

When we look at the statistics for average happiness in Figure 8, we see a similar picture as for the processing time. Hence, the reduction in processing time is accompanied by a reduction in the average building happiness. This result probably relates to two problems. The first problem is that we are not able to quantify cartographic quality sufficiently - which may result in a lower happiness after the application of expert rules. The second problem is that in some cases rules are learnt that guide the generalisation process not towards the "best" solution. Whereas we assume that the latter problem relates to the stronger termination and validity criteria learnt it is necessary to analyse the first problem in more detail in the discussion section.

5 Discussion

5.1 Improvements

As the above results demonstrate we can clearly obtain an improvement of the building generalisation as a consequence of the introduced rules. Thereby the particular strength of the expert rules is the improvement of the cartographic quality, but also a reduction in processing time could be achieved for the Zurich data. The effect of the application of learnt rules is a reduction in time. The combination of both approaches gives satisfactory results as well with respect to efficiency and effectiveness. Apart from the situation in which the learnt rules propose a cartographically not acceptable simplification to rectangle for rural buildings (figure 7) a combination of the expert and learnt rules seems to be very promising. Thereby we discovered that the time reduction, achieved for expert and for learnt rules, seems to add up for the combination of rules.

With respect to the introduction of expert rules our supervised building classification procedure (Steiniger et al., in press) has two differences compared to the method presented by Boffet (2001), and Gaffuri and Trévisan (2004). In Boffet (2000) several types of urban blocks are distinguished, e.g. industrial zone, dense and scattered residential and so on. The application of Boffet's concepts to automated map generalisation is presented by Gaffuri and Trévisan (2004). The first difference of our approach is that it is independent from attribute information of the building data since it based only on shape measures describing the building geometry (in contrast, information on building type was available to Boffet). Hence, our procedure can be used for poorly feature coded data, such as buildings directly obtained from photogrammetric image analysis. The second difference is that our classification approach assigns every building separately to an urban context class and not a complete building block. Thus, we are able to generalise a supermarket in a housing area differently than the surrounding residential houses.

5.2 Identified problems

Apart from the positive results given above we also discovered a couple of problems and have to mention an issue which must be considered when evaluating the efficiency. For the expert rules we could notice a reduction in processing time. Obviously, the characterisation and classification of the buildings preceding the generalisation step consumes time as well. Thus, the reduction of processing time in the generalisation step is counterbalanced by the time required for classification. On the other hand, the pre-processing needs to be carried out only once, while generalisation may be executed many times for different map products.

The probably most important problem which we discovered during our experiments is the inability to sufficiently formalise cartographic quality. From the statistics in figure 8 showing the average building happiness after the generalisation we can discover a decrease of the happiness after the application of the expert rules. To further analyse this result we visualised the differences of the happiness values in figure 9. It is noticeable that for the majority of the

Figure 9. Comparison of the happiness values reached for generalisation without rules vs. with expert rules for the Zurich data. The happiness for the generalisation solution with expert rules is lower, but actually cartographic quality is better. (Data courtesy of Geomatik + Vermessung, City of Zurich)

buildings the happiness has not changed (light-grey fill), which is reasonable, since most buildings were classified as urban and we did not apply specific rules to urban buildings. However, for some industrial & commercial buildings and inner city buildings the happiness has decreased (grey to dark grey fill), although visual inspection suggests that a better cartographic representation is achieved or subsequent building and road overlaps are prevented. This is most often caused by an unsuitable weighting of the defensive concavity constraint and the active squareness constraint in the calculation of the happiness. We would like to give hints for potential solutions, facilitating a future detailed analysis and more tests.

Excluding the squareness condition generally from the calculation for these types of buildings is not recommendable since some walls of the buildings may need to be made orthogonal (e.g. in cases where the wall is not parallel to a road) or more simplified. However, we believe that a local structural analysis (Steiniger and Weibel 2005) and the development of a specialised squareness constraint and specialised generalisation algorithms may solve the problem. With respect to the use of the concavity constraint one should consider to differently weight the concavity constraint and to introduce further shape preserving constraints as presented by Bard (2004). Such constraints can, for instance, penalise solutions by reducing the happiness if a building is represented by a rectangle.

A problem which subsequently emerges from the lack of detail in formalisation appears for the machine learning of rules. If we learn from the reference generalisation (with or without the expert rules) and the learning process tries to optimise the happiness function, then rules can be obtained that cause cartographically unacceptable solutions. Thus, for the learning part we must ensure that the best cartographic solution is always described by the highest happiness value.

Finally a note should be made with respect to the generalisation algorithms of the *Radius Clarity*™ software used in the experiments. We found that the simplification algorithm (A2) sometimes returns inadequate solutions. Here we see a need to either try out other algorithms, with a similar objective, or to adapt the current algorithm to specific cases. If different algorithms and different parameter settings should be included, then further constraints need to be applied which better describe the requirements of cartographic quality than the currently used set of constraints. This would require a ranking between the solutions of different simplification algorithms on a finer scale. A solution with multiple algorithms does also raise the need for machine learning rules and the introduction of expert rules since every branch of the tree of possible solutions (figure 4) will receive a new sub-branch if a new algorithm is added and if no heuristics are applied.

6 Conclusion and outlook

Automated procedures for the generalisation of topographic maps are increasingly integrated in the production lines of national mapping agencies. Apart from the external (customer) requirement to deliver timely mapping data for a reasonable price also internal requirements are imposed on such automated methods to be feasible for the production environment. Two of these internal requirements are to produce maps with a cartographic quality close to that of traditional, "hand made" maps and the ability to process large amounts of geo-data in acceptable time. Our work aims to improve the current approach on automated building generalisation with respect to these internal requirements. In particular, we focus on improving those systems that represent the state-of-the-art in automated map generalisation: self-evaluating systems based on the multi-agent paradigm. In order to make the generalisation process more effective, that is to obtain a better cartographic quality, we introduced – previously not utilised – cartographic expert knowledge. To this end the expert knowledge has been formalised in terms of different building generalisation rules for different urban context classes. Although we restricted ourselves to using generalisation algorithms that apply only to single buildings we enable a context adapted generalisation of buildings as it is recommended in the cartographic literature (e.g., SSC 2005). An improvement of the efficiency of the generalisation process could be achieved by the utilisation of machine learning techniques. With such techniques we learnt rules which guide the generalisation system faster to the “best” cartographic generalisation solution. In the experimental part two building data sets have been generalised from 1:10 000 and 1: 15 000 to 1:25 000 map scale. We could obtain satisfactory results with respect to the two objectives for learnt and expert rules. Moreover we can recommend a combined approach which uses expert and learnt rules since the rules are not in conflict with each other and the generalisation results in our experiments were cartographically satisfying and computationally significantly faster.

During the experiments we also discovered problems in the ability to formalise, by means of constraints, the cartographic requirements for graphical quality. We see here clearly a need for future research to better define shape constraints and parameter settings to ensure that the happiness values computed on the basis of constraint satisfaction indeed express the cartographic quality as it is visually experienced in reality by the map reader. This will help to improve the generalisation results on the one hand and on the other hand the learning approach will return better rules for a well defined objective function.

Other issues for further research can be identified as well. In our experiments we only considered constraints acting on individual buildings, which is largely sufficient for our target scale of 1:25 000. Thus, a next test should consider larger scale reduction factors, such as from 1:25 000 to 1:50 000 and 1:100 000. Here, we see even more potential to influence the control and selection of generalisation algorithms based on the urban context classes, since more topographic detail needs to be reduced (Müller 1990) and hence, more contextual generalisation operations are necessary. Thereby one should not only focus on the generalisation of buildings but may also control the generalisation of other object classes, including roads. For instance, Edwardes and Regnauld (2000) outline an approach for the differentiated generalisation of roads in urban, inner city and rural areas.

Finally, as a further research objective one should try to include in the urban classification semantic information where it is available, as exemplified by Boffet (2001, 2000), who used information on industrial/commercial areas. This will help to identify misclassified buildings and enables to introduce specific generalisation rules for objects of particular interest like hospitals.

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D. Research Paper 4

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Recognition of Island Structures for Map Generalization

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ABSTRACT
In this paper we describe work on the automatic recognition of island structures. In an initial phase several test persons were asked to mark groups of islands that they perceived on test maps. Based on these experimental results the island structures were categorized with respect to size and shape, and their construction described using principles from Gestalt theory. Based on those descriptions of island structures we will present an algorithm for the detection of large groups of islands based on a Minimal Spanning Tree (MST). Therefore, we apply split and merge operations on the MST. For the automated characterization of the shape and orientation of island groups we propose to use principal components obtained from a PCA. The results of the algorithm are then visually compared with the island groups previously marked by test persons and shortcomings of the approach are discussed.

Categories and Subject Descriptors
I.4.8 [**Image Processing and Computer Vision**]: Scene Analysis – *object recognition.*

I.5.4 [**Pattern Recognition**]: Applications – *computer vision.*

General Terms
Algorithms, Experimentation, Human Factors, Theory.

Keywords
Polygon patterns, map generalization, perception, Gestalt theory, proximity graphs, minimal spanning tree, cartometrics.

1. INTRODUCTION
In automated map generalization research various authors [4, 10] have stressed the role of structure recognition or cartometric analysis as a key step placed at the beginning of the automated generalization process. The main objective of the structure recognition stage is to identify situations (structures) of special importance and select the corresponding objects for an appropriate treatment during map generalization. For instance, islands or lakes forming the outline or the core of a structure should never be eliminated [2]. On the other hand isolated islands should not be eliminated as well since they may be an important point of orientation for map users. These two cartographic rules, which are applicable to real-time generalization of internet map services (e.g. Map24.com) as well as to conventional paper map production, should highlight the necessity of structural recognition in map generalization. If these rules are not considered, the general pattern of spatial arrangement of islands or lakes will be lost, as can be seen on any internet map server lacking generalization facilities.

Research on cartographic pattern recognition has gained increasing attention in automated map generalization. Much of that work, however, was devoted to the discovery of building structures and road patterns (e.g. building alignments, building clusters, settlement partitioning) in urban settlements [3, 12, 7], due to the importance of the built urban environment in topographic mapping. Less work has addressed the problem of identifying important structures in the natural environment. Müller and Wang [11] presented an approach for the generalization of area patches (islands) and noted that their implementation was not able to preserve archipelago structures. Already earlier in the 1960's Bertin [2] emphasized the importance of preserving patterns of groups of lakes in map generalization and presented a manual approach which maintains the structures he considered as important.

The focus of this paper is on describing a procedure for the recognition of perceptually important island structures. This approach is intended to represent the structure recognition stage for the generalization of islands in topographic and thematic maps. The structure recognition process basically entails four steps which will be explained in the remainder of this paper:

1. Identifying the important situations (i.e. island structures), discussed in Section 2 and 3.
2. Formalizing the situation (describing the structures by their construction principles), Section 4.
3. Developing a structure recognition algorithm, Section 5.
4. Developing evaluation procedures, Section 6.

Developing detailed application scenarios for map generalization will be part of our future research and is therefore not presented in this paper.

2. WHAT ARE ISLAND STRUCTURES? – THE IMPORTANCE OF BEING SPECIAL

Map generalization aims to preserve typical structures during scale reduction and to emphasize important elements while suppressing the unimportant. The importance of map objects as well as characteristic map objects are usually intrinsically given by the map purpose. Thereby, more specifically, importance is defined by *semantics*, e.g. a supermarket in a housing area, or by its context with respect to map user *perception*, e.g. a large building among a group of small houses. Important elements can be either single map objects or small groups of objects. In contrast the typical elements are not outstanding single objects or small groups of objects; rather they are made up of larger number of objects which give the map an ordered overall structure. With respect to our goal of generalizing islands in topographic (and thematic) maps we need to detect on one hand the outstanding single islands and on the other hand the typical (large) and the special (small) island structures. The task which now appears is to formalize such structures and extraordinary islands. Since natural islands have been shaped by tectonic and geomorphologic processes one of the main objectives will be to preserve geomorphologic forms and patterns during generalization. Hence, an initial idea might be to use elevation information and to detect and generalize structures similar to those which are important for relief generalization [17]. However, as we are only dealing with 2-D map data, we have to restrict our procedure to the recognition of 2-D shapes and patterns. We need to go another approach, based on principles of perception.

Gestalt theory has extensively dealt with the rules which let humans perceive groups rather than single objects. Especially Wertheimer [18] identified a number of *laws of organization in perceptual forms*. We argue that the two most relevant laws with respect to map reading and generalization are the *Law of Similarity*, describing homogeneity among the members of a group, and the *Law of Proximity*, describing that a group is formed by nearness of the group members to each other compared to other objects, not being part of that group. We consider them the most relevant laws since they have been used by several researchers, to some extent subconsciously, for the recognition of building alignments in map generalization [16]. The laws give us some idea what is important for grouping islands. However, we neither do know how to rank Gestalt properties such as size, shape and orientation against each other for groups formed by similarity nor how to put similarity in relation to spatial proximity. Therefore we decided to make an experiment where people were asked to mark groups of islands on maps. The experiment and a typification of island structures based on the results are described in the next section.

3. AN EXPERIMENT: WHAT'S AN ISLAND STRUCTURE TO YOU?

A test with people of the GIScience center at the University of Zurich was carried out to identify a basic set of island groups. In more detail the experiments should answer the following questions:

1. Which types of island structures are perceived?
2. Which (cognitive) approaches are used to group islands?
3. What are the common properties of the members of an island structure?

These three questions will be addressed in subsections 3.2.1 to 3.2.3. The first question should help to classify the identified island structures. Answers to the second question may give hints which pattern recognition methods can be useful to automatically detect the structures. Finally the last question should help to identify measures and rules for the grouping process.

3.1 Test material and procedure

A pencil and paper test has been performed by giving each test person a map showing the islands of the study area of Figure 1. The person was then asked to mark groups of islands of which he/she thinks they belong together. Additional information given to the test participant included three notes: First, that the test area is near the Åland Islands between Finland and Sweden; second, that these patches were skerries and islands originally formed by glacial processes; and third, that islands structures might exist at different scales. More precisely there could be large groups of dozens of islands and small groups of only a few islands. In case that a person wanted to mark such differently sized groups we provided pens of different colors. The time for marking the islands groups was not restricted but took between 5 and 10 minutes. Overall we performed the experiment with 13 persons. Half of the participants (7) were geographers and the other half had a background in geodesy, physics and computer science, respectively. The number of 13 participants may not be sufficient for statistical evaluations but should be adequate to make qualitative statements.

3.2 The study area

As already mentioned above the study area is near the Åland Islands. More correctly the islands are located between the Finnish southwest coast and the Åland Islands (see Figure 1). The archipelago consists of skerries, small rocky islands too small to be populated, and other islands formed during the ice age. The Finnish island data were extracted from the ESRI Data & Maps media kit. Since these vector data do not contain information about

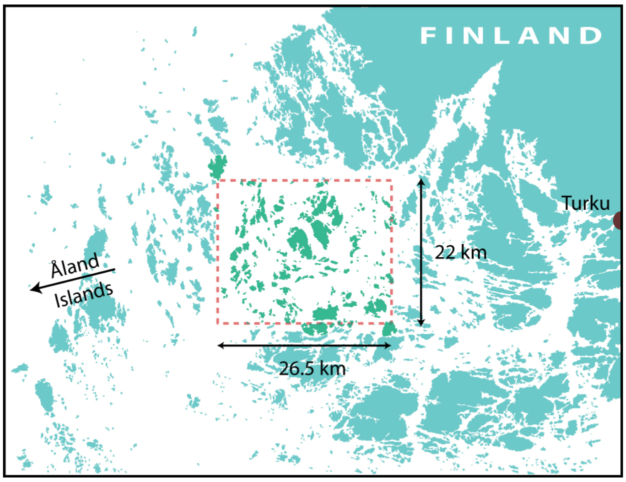

Figure 1. Test data for recognition of island structures. The islands in the box are part of an archipelago south west of Finland. Data © by ESRI.

the spatial resolution, we estimated from the smallest depicted island (with an area of ~5000 m^2) that the resolution is in the order of a map scale 1 : 360 000. Very small islands must therefore have been already eliminated from the dataset.

To ensure that the selection is not built of random structures we generated histograms to inspect the distributions. We created histograms for three measures: polygon area, fractal dimension, and orientation. The orientation measure used is described in [6] and is defined as length weighted mean orientation of the polygon edges. The area histogram shows a one-sided normal distribution and the fractal dimension a normal distribution. The histogram of the orientation shows approximately a uniform distribution with two strong peaks, one for the north-south and another one for the east-west direction. These peaks seem to be due to the glacial genesis. Apart from these peaks for the orientation histogram, the distributions are as expected. Therefore we conclude that no random island patterns are contained in the dataset.

3.3 Survey results

The evaluation of the results consisted of two parts. On the one hand, we reviewed the notes made during the experiment which describe the approach to mark the structures. On the other hand, we analyzed the drawings to demarcate the island groups. In order to facilitate the formalization of islands structures we integrated the drawings of the individual test persons. After selecting the basic set of "core" groups we drew them on a new plot and counted the number of people who found a particular structure. This plot, containing the common set of identified patterns, is shown in Figure 2. The marked groups were then evaluated with respect to the three questions given above.

3.3.1 Types of island structures

Two main criteria to typify the marked zones were used by the test persons. One criterion is the shape, the other one the size of the island groups. With respect to shape compact and elongated island groups can be distinguished. With respect to size we can identify at least small (micro) and larger (meso) groups of islands, as it was also suggested by the comments of the test participants. At least four persons introduced additional size levels for the island groups. But here it is difficult to extract reliable limits for the number of islands defining a size level. Rather the levels are given implicitly through part-of relations, whereas a large group can be subdivided into smaller groups. Such a part of relation is for instance visible in Figure 2 and denoted with A. In summary for the study area the persons found approximately five large groups, which we will call meso-structures, where three have compact shape and two have an elongated shape. Apart from the meso-structures about 14 small groups, which we will call micro-structures, have been discovered. Here, less than a third can be described as compact, most of them are elongated. The term macro–structure is reserved for very large structures which are usually not perceived without prior knowledge of their existence or generating process [16]. Such a macro-structure is also contained in the test data set. In Figure 1 the study area is shown as part of a large archipelago. Here, one can perceive a curved alignment structure which is also shown as a bold red line in Figure 2.

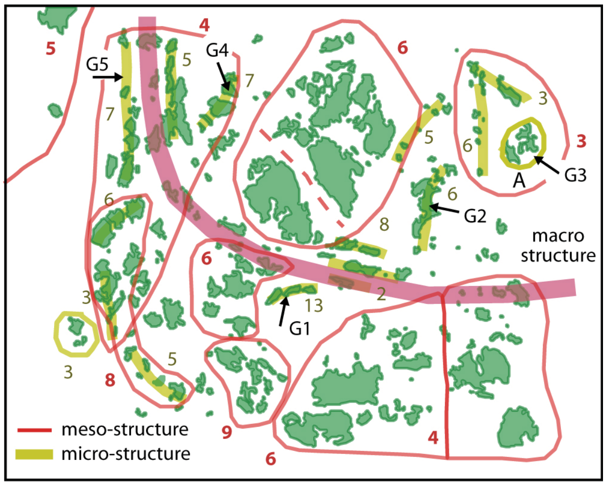

Figure 2. The combination of island structures chosen by the participants. The numbers next to the structures correspond to the number of participants who marked the structure.

3.3.2 Approaches to grouping

Referring to the second question posed above we can assign the participants to three groups according to the mark-up strategy used. The first group, containing nearly half of the people did not show a clear strategy. The second group of five persons used a top-down strategy. They first marked the large island groups and subsequently divided these groups into smaller partitions. Thereby, it was recognized by the test persons that this strategy could not be strictly applied, since some of the micro groups were not considered as being part of a meso structure. Finally the third group, consisting of only 2 persons, used a bottom-up approach, initially forming small groups of islands. Afterwards the two test persons applied a different strategy. One person tried to merge the micro groups, while the other person formed groups from the remaining, not yet assigned islands. Two participants also noted that an object could be part of two or more groups of the same size level.

3.3.3 Member properties of the island groups

The evaluation which remains is the description of the members of one island group. Therefore we analyzed the group with respect to the visual variables of cartography introduced by Bertin [2]. The primary variables are (1) position [x,y], (2) size, (3) shape, (4) orientation, (5) color and (6) texture. The variable color, which often is linked to category, is not relevant since all islands have the same meaning and thus the same color. Also texture is irrelevant for our work since our islands are not textured. All other variables should be considered in the evaluation. Note, that in Gestalt theory the position of objects is usually considered from a relative perspective. Therefore the position variable designates spatial proximity.

With respect to the variables size, shape and orientation the islands within a group show very heterogeneous characteristics. We can find large and small, compact and complex islands with different orientations in the same group. Thus, it seems that spatial proximity is the key criterion for the perceptual formation of large island groups used by the test persons.

The smaller island groups usually have 3 to 6 members. Four participants did form micro-groups of only two islands. In Figure 2 one can see that the groups with 3 to 6 members show in most cases an elongated form and that the spatial proximity to other islands in the vicinity is usually larger than between the members within a group. A deeper analysis reveals that in our dataset at least five types of micro-groups exist. For the first type the islands seem to be of similar shape, size and orientation, such as the group denoted by G1 in Figure 2. The second type is apparently dominated by a larger island. Here, the orientation of the dominating large island seems to define the orientation of the micro structure (G2). The members of the third type seem to show few commonalities (G3). The only criterion forming these groups is spatial proximity. Hence, these groups have in most cases a compact shape. Finally the fourth and fifth type of micro-structure may be considered as special cases. Probably the islands of group G4 have been considered as group because the composition is approximately symmetric. Symmetry in the group composition is also described in one of laws of organizations by Wertheimer [18]. This *Law of Good Gestalt* (good continuation principle) refers to group properties which support the process of grouping. Besides similarity these properties are simplicity, closure and equilibrium. In terms of the orientation of the groups we see that some have an approximately vertical direction. It is known from psychology [1], and also mentioned by Wertheimer as the *Law of Prägnanz (Law of Conciseness)*, that visual perception is more sensitive to natural cardinal directions. This implies a better support for the mental grouping of objects into these directions. The consequence for pattern recognition is that special attention should be given to horizontal and vertical alignments, being aware that the spatial proximity principle may be overridden by the *Prägnanz* principle. An example for such a micro group may be G5.

4. FORMALIZATION OF ISLAND STRUCTURES

After we have tried to describe the meso- and micro-structures found by the participants of our test, the next step is to build a catalogue of structures which we aim to detect. In the previous subsection we introduced the notion of micro-, meso-, and macro-structures, relating to group size. From the test results we conclude that micro-structures do consist of 2 to 10 islands, while meso-structures usually contain more than a dozen of islands. Macro-structures finally are very large island compositions which can involve several meso-structures and are usually not perceived without knowledge of their existence. Thus, their constitution can be linked to Wertheimer's *Law of Past Experience*. Shape, the second classification parameter, describes the characteristic shape of a group, which one perceives from the so called *Structural Skeleton* [1, 16]. Basically it seems to be useful to distinguish compact groups and elongated groups. We will call the former *clusters* and the latter *alignments*.

In the early work reported here, we have focused exclusively on the detection of meso-structures. Thus, we only address the principles forming larger island groups. If we consider our analysis results in Section 3.2.3 we conclude that island structures on the meso level are based only on a single perceptual principle, which is spatial proximity. Other principles may influence the map readers perception but can not be applied to all meso-groups depicted in Figure 2. Therefore we will present in the next section an automatic approach for the detection of meso-structures based only on the evaluation of spatial nearness.

5. DETECTING MESO STRUCTURES OF ISLANDS

5.1 Algorithm sketch

From the previous section we know that meso-structures are mentally formed based on a key principle which is spatial proximity. Thus, the members of one group will have shorter distances to each other than to islands which are not part of that group. Here, we should additionally stress that spatial proximity is a function of the size of the object on which one does focus. This has also been emerged from the experiment. Recognition algorithms for distance based grouping of objects include among others hierarchical agglomerative clustering approaches [9] and distance based graph structures. Inspired by the work of Regnauld [13] who applied a graph based approach for the recognition of building groups we decided to extend from his results. The advantages which this approach shows over a clustering approach will be discussed below. The procedure to detect the meso-structures consists in principle of the following six steps:

1. Create from the input set of islands a Dynamic Proximity Graph which connects every object with every other object within a certain neighborhood. The output from this procedure will be several large and small groups of islands, whereby isolated islands will not be part of the graph structure (Figure 3-B).
2. Reduce the proximity graph to a Minimal Spanning Tree (MST). Here we will obtain the structural skeleton of connected islands, that is, the islands will be the limbs of a chain. The advantage of forming a chain is that we only need to split it in specific points to obtain the meso groups. (Figure 3-C).
3. Select seed islands, which are part of the MST and will form a set of potential cores for meso-structures. (Figure 3-C)
4. Create Voronoi polygons from theses seeds and trace the MST from every seed to find the connected islands. The tracing will stop at the edges of the Voronoi regions. After this procedure we will obtain an initial set of meso-structures whereby the grouped islands will be within the Voronoi region. (Figure 3-D).
5. Extend the meso-structures by adding all remaining islands which are connected to only one meso-group. (Figure 3-E).
6. Finally merge those meso-structures whose seed islands are within a certain neighborhood to each other (see Figure 3-F). The neighborhood can be defined similarly to the neighborhood used in the first step.

After these six steps we obtain as primary output a certain number of meso-structures, whereby the islands of each group are still connected to each other by the graph structure. This will make it easier to handle the groups in further processing stages, e.g. for characterization or use during map generalization. As secondary output isolated islands are obtained which will not be part of any structure. Here, it might be useful to reconnect some of them to a meso-structure, for instance, if they fall within the convex hull of a meso-group.

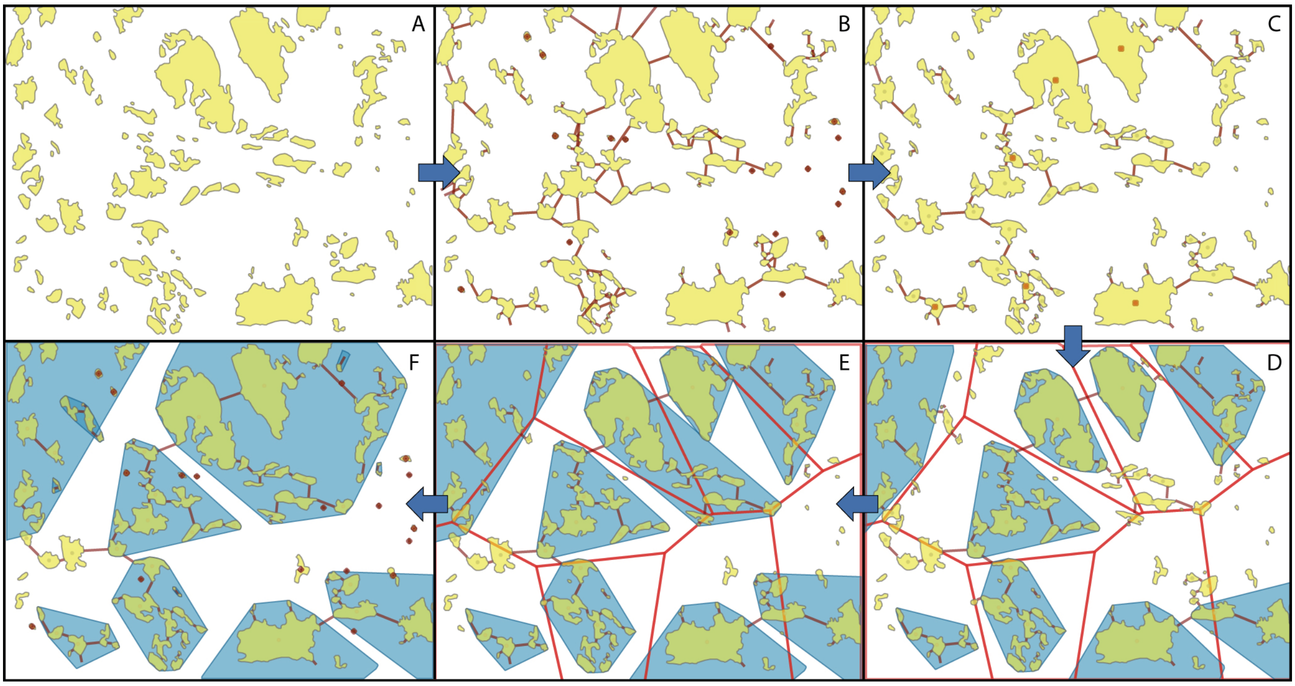

Figure 3. The steps of the meso-structure detection algorithm: A) original islands, B) dynamic proximity graph and excluded isolated islands C) Minimal Spanning Tree (MST) and seed nodes for candidate groups, D) Voronoi regions of seeds and candidate meso groups, E) extended meso groups, F) final meso-structures after merging.

The chosen graph based approach shows several advantages. Firstly, the approach to use a MST is scale free. Although parameter exists (as described below) they need not necessarily be defined with respect to the map scale. Secondly, comparing the graph approach with an agglomerative clustering approach, one needs not to define the final number of clusters. And thirdly, small clusters consisting of only one or two islands are already separated in the beginning and will not further influence the grouping process. In the following subsection we give some more details of the algorithm, which is necessary to evaluate the limitations of the approach in Section 6.

5.2 Algorithm details

5.2.1 Creating a dynamic proximity graph & MST

The proximity graph used for the algorithm is an extended version of the data structure described in [14]. What the algorithm does is basically to connect every object with every other object if the connection is below a threshold distance. The specific property of the proximity graph is that the distance between polygonal objects is not calculated between the centroids. Instead the real distance from polygon outline to polygon outline is used. Hence, this graph structure accounts for object size and spatial proximity between the objects. The graph used by Regnauld [14] has a fixed distance threshold. We introduced the distance limit as dynamic parameter and therefore called our version a dynamic proximity graph. This threshold d_{max}, defining the search neighborhood around a polygon, depends in our version on the size of the polygon itself. The value of $d_{max}(p)$ is calculated: $d_{max}(p) = k \cdot r(p)$. Where $k \in \Re$ is a constant, chosen according to the perceptual recognition limit, and $r(p) \in \Re$ is a radius calculated from the actual polygon. The constant k is assumed to simulate a view horizon of the eyes in which a person still recognizes objects if focusing the view on the center object. For the determination of the radius $r(p)$ we tested two different models. In one variant we calculated the radius from the area of the polygon by comparing it with a circle of the same area. In the second variant the radius has been defined as half the longest edge of the minimum bounding rectangle (MBR) of the polygon, as illustrated in Figure 4. Hence we obtain a sphere of influence which is proportional to the polygon's perceptual weight.

A second constraint apart from the maximum distance has been introduced. This constraint removes edges, if the connection is established only from one polygon to another and not in both directions. This happens if a small polygon is in the influence zone of a large neighbor polygon but the influence zone of the small polygon is too small to reach the large polygon. This case is illustrated in Figure 4 and denoted with B.

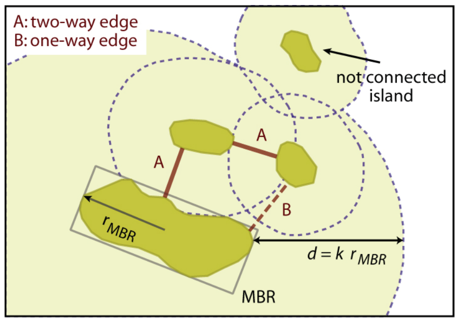

Figure 4. Construction principle of the dynamic proximity graph with two-way edge condition shown on four islands.

In the second step of the algorithm we derive from the proximity graph the MST. This tree structure was first utilized for Gestalt based recognition by Zahn [19] to detect point clusters. Regnauld [13] used this structure for the recognition of building clusters. For our algorithm we used the unmodified implementation of [14]. The resulting node-edge image for islands or building patterns comes quite close to what is called by Arnheim [1] the structural skeleton. Thus the analysis of the MST could be used to characterize the shape of meso-structures, although we will later present a different approach.

5.2.2 Selecting seeds, splitting the MST and creating candidate meso-structures

To split the chain of islands represented in the MST into smaller fractions which correspond to the desired meso-structures we need to define appropriate split points. In our approach the split points are implicitly defined as points resulting from the intersection of a line drawn at half distance between the seed objects of two meso-structures and the MST. Therefore we need to define the seed or core objects of possible meso-structures. Assuming that meso-groups have usually a clustered shape, such seed objects must be central and well connected within the meso-group. If one does overlay the reference meso-groups from our experiment and the MST, then one can observe that the centers of the meso-groups correspond to nodes of the MST which have at least four connections. Therefore we used the number of connections of an MST node as criterion to be a seed node for a particular meso-structure. An interesting fact to note is that the criterion of good connectedness does often coincide well with the size of the objects. Thus, within the MST large objects with central position will usually be also well connected objects.

As we have now selected our seed objects we could calculate the split points and add all islands between the seed and the split point to a meso-structure. It is difficult to calculate the split point and assign the islands to the meso-groups if the traces from three seeds meet in one MST node (case not shown in Figure 3-C). Therefore we went another approach. The alternative approach is to define the influence zone for every seed node by calculating its corresponding Voronoi polygon [5]. We can then trace the MST and add all islands within the Voronoi region of a seed (see Figure 3-D). After the first tracing, we extend the structure with all islands which are connected with only one seed node and not yet part of the structure (see Figure 3-E). As a result of this process a few islands will not be assigned to any of the structures, e.g. the ones in the center of Figure 3-E. This can not be avoided as it is unclear to which of the surrounding groups they should be connected. Comparing with the results of the perceptual experiment we observe that the participants usually did also not assign such 'lonely islands' to a group. Therefore we leave them unassigned, but should also consider forming a new group if they are connected to each other.

5.2.3 Obtaining the final meso-structures

The result of the previous stages is a set of candidate meso-structures where the seed points can be very close to each other or directly connected. Thus, from a perceptual point of view it makes sense to merge such structures, if the influence zone of one seed polygon touches or overlaps another seed polygon. The influence zones are calculated like in the beginning using d_{max} either based on the MBR length or the area of the polygon.

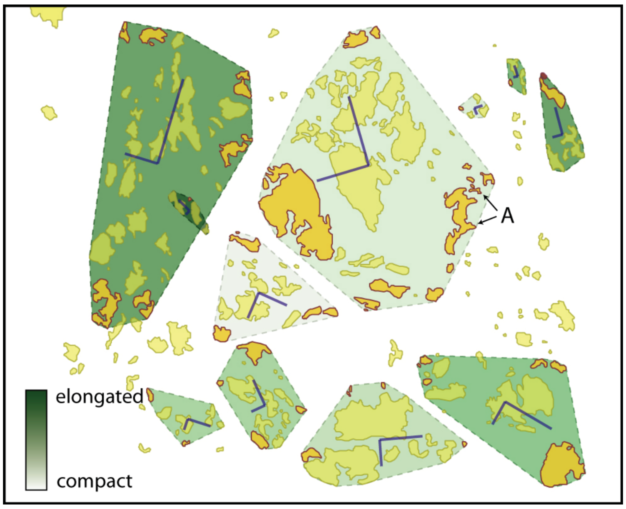

Figure 5. Detected meso-structures and their principal components to describe shape and orientation. Islands with dark outline are outliers of a T^2 test with $\alpha = 0.25$.

6. MESO STRUCTURE DESCRIPTION AND ALGORITHM EVALUATION

6.1 Using the PCA to characterize the meso-structures

In Section 4 we noted with respect to the shape of the structures that a distinction can be made into island *alignments* and island *clusters*. A determination of the *orientation* of the detected groups is of interest if one aims to infer the existence of larger islands patterns, such as macro structures, and for the preservation or even exaggeration of the group characteristics during the map generalization process. A method which delivers the orientation directly and the shape indirectly is the Principal Component Analysis (PCA). For a comprehensive introduction to the PCA we refer to Jackson [8]. If one applies the PCA to a point data set where every point is described by [x, y]-coordinates, the transformation will deliver two principal component vectors. These vectors indicate the two main, orthogonal orientations of the point group. Furthermore, the magnitude of the vectors can be used on one hand to identify the main orientation, which corresponds to the larger magnitude, and on the other hand to determine, on the basis of the ratio of the magnitudes, whether the point cloud is compact or elongated. Figure 5 shows the principal component vectors for every detected meso-structure. The darker (greener) the circumscribing hull of the meso-group the higher the ratio of the magnitudes and hence the more elongated is the structure. As pointed out previously the PCA works on individual points, thus it is necessary to transform the island polygons into points. The simple approach would be to use the centroid as representation of an island, but this approach does not account for the visual weight given by the island's area. Thus, we used the points which describe the outline of an island instead.

6.2 Evaluation of meso-structures

6.2.1 A spatial outlier test

The meso-structures obtained from the approach of Section 5 should be evaluated with respect to their interior homogeneity. This is similar to the application of an outlier test. Hotelling's T^2-statistics, a multivariate generalization of the student t-test has been recommended as a test prior to performing the PCA [8]. However, the application of the test does not depend on performing a PCA and we therefore propose the test to validate the meso-structures. Since spatial proximity has been the exclusive group forming principle we need to check the group for outliers in the spatial domain only. The confidence limit, defined by the user will form an ellipse; those main axes are similar to the principal component vectors. Points outside the ellipse are considered as outliers. We have applied the T^2-test to the meso-structures in Figure 5. Similar to the PCA the input values are the coordinates of the points defining the outline for every island. The islands marked in Figure 5 with a dark border are the resulting outliers for the error probability of $\alpha = 0.25$ and the condition that an island is considered as outlier if half of its points are outside of the confidence ellipse. Since we are still in an experimental phase we can not yet explicitly recommend how to best exploit automatically the information about potential outliers in subsequent steps. Therefore, at this point, we only propose to check the outlier islands further whether either a few of them are connected or one a certain size of the area is exceeded. If this occurs it could be useful to split these islands from the meso structure, and particularly in the first case, let them form their own meso-group. For instance, this could be done with the island group denoted with A in Figure 5.

6.2.2 Comparison of experimental and detected meso-structures

Above we proposed an evaluation approach to be used during the recognition process. Now we shall evaluate whether the algorithm actually delivers, that is, whether it groups a given set of islands into large island structures similar to human perception. Hence we need to compare the algorithm outcome with the set of meso-structures identified by the participants of the perceptual experiment described in Section 3. The evaluation is done visually based on the overlaid results (see Figure 6). The parameter k of the perceptual horizon has been set to $k = 3$. For both distance calculation variants (polygon area dependent and MBR dependent) the detected structures are similar to the human results of the experiment. Basically the cores of the groups do overlap, but the extents vary, that is the decision which island is still part of one group is different between algorithm and human results. But in the context of this statement we have to mention that the problem of similar group cores with different extents did equally appear in the results of the test persons. From this perspective—and considering that this is still ongoing work—the algorithm results are encouraging, with one exception. This exception concerns the extent of the large cluster in the center of the image. Both algorithm versions add to the meso-structure the left-hand island group which has been considered by the users as separate micro-structure, which can be seen in Figure 2. Probably the spatial outlier test described in the previous section will help to identify such situations, enabling to separate this island group from the larger one. If one compares between the algorithm versions differences exist in the extent of one meso-group and in the number of meso-structures on the left. Here again the results from the human experiment have been also very different with respect to both, the extent of the lower right meso-structure and the number and shape of large groups on the left. Hence, one cannot say that one algorithm variant is better than the other. To our understanding, as expressed in [15], structure recognition for map generalization should only propose sense making structures. The ultimate decision on acceptance of such a proposal has to be done by the human expert. Thus, it is from our point of view not necessary to discard one algorithm version and we rather recommend testing both algorithm variants.

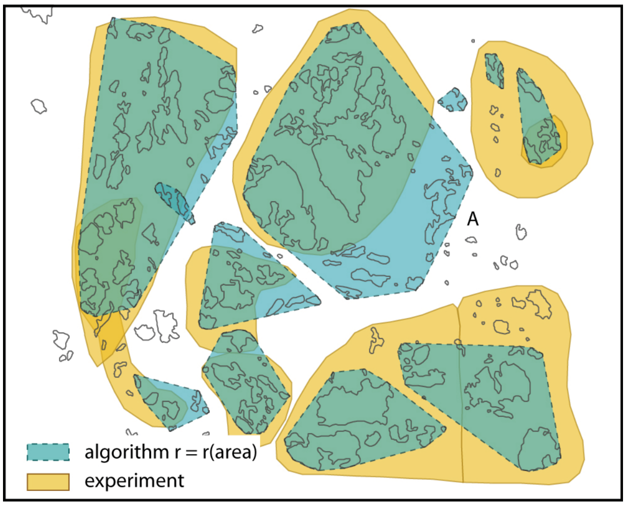

Figure 6. Results of the detection algorithm for meso-structures overlaid on the islands groups perceived by the participants of the experiment.

6.3 Limitations of the algorithm

The presented algorithm to detect large island structures works appropriately in comparison to human experiments, as pointed out in the previous subsection. Similar results have been obtained for two other test dataset. However, at least two shortcomings exist presently. The first is that the user has to define the parameter k for the creation of the proximity graph. For our test data the value $k = 3$ worked well. However, the problem that the large meso-group in the center of the test area aggregates the left-hand micro-group (denoted with A in Figure 5), does show that a fine tuning is necessary. This can happen during the processing in either decreasing the parameter k, here the large islands will not be connected anymore; or by selecting the right large island (left of A in Figure 5) as further seed point. Applying a post processing strategy one could split the group again after the outlier test as a third variant. The second weakness of the proposed approach relates to the selection of seed points for the candidate structures. Currently we did choose all islands having at least four outgoing edges in the MST. Thus, a single small island either added to the large island in the previous example or removed from a seed island of the meso-group on the left side in Figure 6 may change the results dramatically. Thus, priority for future refinements must be given on finding a more robust method to define the seed islands for the candidate meso-structures.

7. FUTURE WORK

This paper reported on work on the automated recognition of large island structures for map generalization. The work is still ongoing. Objectives for our future research emerge especially from the evaluation in the previous section. The comparison of the human results with the island groups formed by the algorithm shows that a splitting of large groups should be considered. Therefore it seems to be useful to develop a split procedure based on the outlier detection presented in Section 6.2.1. The evaluation of the grouping procedure revealed that the current seed selection method based on the MST edge connection is not sufficiently robust to small changes in island configurations. Hence, alternative selection methods have to be explored. A further point of interest is a better shape analysis for elongated island structures. Here it is useful with respect to the map generalization process to distinguish between curved and straight island alignments. Such an advanced method could be based on the analysis of the MST edges, forming the structural skeleton. Apart from these improvements the next major objective is to develop recognition algorithms for the micro-structures. This objective demands to further analyze the forming principles of such structures. Our evaluation of the user test in Section 3.3.3 has shown that principles of Gestalt theory may form a sound base to accomplish this task. Finally, once the algorithms for detection of micro- and meso-structures have been developed and validated on a range of different study areas with different characteristics, it will be necessary to specify and test application scenarios during the process of automated map generalization.

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